Evolving Insect Locomotion using Non-uniform Cellular Automata

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Abstract

This article presents a model for the evolution of locomotion behavior in a simulated insect. In our model, locomotion is defined over a discrete state space using non-uniform cellular automata. The architecture of the model is inspired from the distributed model for leg coordination proposed by Cruse. We apply a genetic algorithm to a population of non-uniform cellular automata to evolve locomotion behaviors. We demostrate that this model can be used to evolve several commonly observed gaits of insects. Additionally, we show that the evolutionary process yielded periodic attractors which are invariant from the initial conditions.

Introduction

The problem of insect locomotion has been approached with several methods. Brooks (1989) has used a subsumption architecture in building a robot that walks. Beer (1990) has used a recurrent neural network to control locomotion in a simulated insect. Spencer (1994) has demostrated that genetic programming can be used to evolve locomotion with a minimum of assumptions about how walking should occur.

Some insect inspired locomotion models suggest that locomotion may be viewed as an emergent property of local interactions between the mechanisms responsible for the control of individual legs (Ferrell 1995). These models share several properties with cellular automata: parallelism, locality of interactions and simplicity of components. We use this observation in building a model based on non-uniform cellular automata. The model gives a simulated insect the ability of walking.

Previously, cellular automata have been applied to the study of many different emergent collective phenomena (Gutowitz 1991). More recently, cellular automata have been used as the foundation of artificial life models (Sipper 1995). We propose the use of cellular automata for the synthesis of agent behaviors.

Research in autonomous agents has focused for many years on the design of computational models capable of synthesizing agent behaviors. Pfeifer and Scheier (1999) argue in favor of parsimony when modeling agents: if there are a number of competing models, the more parsimonious ones are to be preferred. Cellular automata are general and simple (Sipper 1995). Additionally, they provide a formal framework for understanding the emergent and dynamical properties of agent behaviors. However, the design of the cellular automata local interaction rules to perform global computation can be extremely difficult to accomplish.

Das, Crutchfield, Mitchell and Hanson (1996) have demostrated that an evolutionary process can be used to produce globally coordinated behavior on a distributed system. Using a genetic algorithm to evolve cellular automata, they showed the evolution of spontaneous synchronization and emergent coordination.

In our model, locomotion is defined over a discrete state space using non-uniform cellular automata (Sipper 1997). In non-uniform cellular automata, the cellular rules not need to be identical for all cells. The architecture of the model is inspired from the distributed model for leg coordination proposed by Cruse (1990). We apply a genetic algorithm to a population of non-uniform cellular automata to evolve locomotion behaviors. Our results indicate that this model can be used to evolve several commonly observed gaits of insects, including those resulting from amputation.

We demostrate that a simple, parsimonious model based on non-uniform cellular automata is capable of explaining the essence of coordination in locomotion behavior. Additionally, we show that the evolutionary process yielded periodic attractors which are invariant from the initial conditions. These periodic behaviors represent general solutions to the insect locomotion problem.

Insect Locomotion

Insect locomotion is notably robust and flexible. Insects can walk over a variety of terrains. In addition, they can also adapt their gait to the loss of up to two legs without serious degradation of performance. To provide support and progression, the movement of the legs must be coordinated by the locomotion system (Beer & Chiel 1995).

Wilson (1966) defined several terms associated with insect locomotion:

Protraction: The leg moves towards the front of the body.

Retraction: The leg moves towards the rear of the body.

Power stroke: The leg is on the ground where it supports and then propels the body. In forward walking, the leg retracts during this phase.

Return stroke: The leg lifts and then swings to the starting position of the the next power stroke. In forward walking, the leg protracts during this phase.

Anterior extreme position: In forward walking, this is the target position of the return stroke.

Posterior extreme position: In forward walking, this is the target position of the power stroke.

Cruse (1990) developed a model that employs stimulus and reflexes to generate leg motion and gait coordination. There are three basic excitatory and inhibitory influences responsible for the coordination between the legs. These influences affect the threshold for beginning the return stroke by adjusting the posterior extreme position of the receiving leg. It has been shown that these three influences provide the necessary and sufficient conditions for sustained movement.

The distributed model for leg coordination proposed by Cruse may be viewed as a *dynamical system* in which the set of the state variables consists of the positions of the legs and their corresponding extreme positions at every time step. The *dynamical law* of the system can be formulated in terms of the excitatory and inhibitory influences received by each leg.

This perspective of the locomotion model shares several properties with cellular automata: parallelism, locality of interactions and simplicity of components. Also, cellular automata are dynamical systems. We use this observation in building a locomotion model based on non-uniform cellular automata.

The Model

The artificial insect we use is based on the model proposed by Beer (1990). The design of the body of the artificial insect is shown in figure 1.

The insect can raise and lower its legs, and is assumed to be constantly moving. That is, when the insect raises one of its legs, a protraction movement is automatically activated. Similarly, when the insect lowers one of its legs, a retraction movement is automatically activated. Finally, both the return stroke and the power stroke are assumed to terminate in one time step. The return stroke has no effect when the leg is positioned at its anterior extreme position. Similarly, the power stroke has no effect when the leg is positioned at its posterior extreme position.

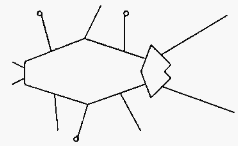

Figure 1: Artificial insect (Beer, 1990)

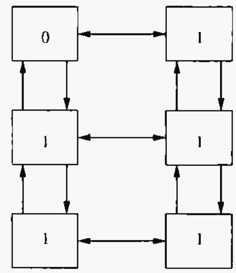

Figure 2: Cellular automata locomotion model

In this work, we conceive locomotion as an emergent behavior. Locomotion emerges as a result of the interaction of two non mutually exclusive behaviors: support and progression.

The artificial insect exhibits the support behavior at any time step if the polygon formed by the supported legs contains the center of mass of the body (Beer 1995). The artificial insect exhibits the progression behavior if the legs are coordinated over a number of time steps in order to move the body of the insect.

The distributed model for leg coordination is modeled using a non-uniform cellular automaton consisting of six cells: L_1, L_2, L_3, R_1, R_2 and R_3. Each cell is a possible different finite state machine that transits between power stroke and return stroke depending on the state of the adjacent cells. Each cell assumes a "0" state during its return stroke and a "1" state during its power stroke. An example configuration of a cellular automaton is shown in figure 2. In this configuration, cell L_1 is in its return stroke and the other cells are in their power stroke.

The neighborhood state function g of each cell α is determined by the direction of the influences indicated

α	$g(\alpha)$
L_1	$\{L_2, R_1\}$
L_2	$\{L_1, L_3, R_2\}$
L_3	$\{L_2, R_3\}$
R_1	$\{R_2, L_1\}$
R_2	$\{R_1, R_3, L_2\}$
R_3	$\{R_2, L_3\}$

Table 1: Neighborhood state function

L_1	L_2	R_1	L_1
0	0	0	1
0	0	1	1
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	0
1	1	0	0
1	1	1	1

Table 2: Transition function for cell L_1

in the distributed model for leg coordination proposed by Cruse. Table 1 shows the fuction g.

We define 28 configurations in which the insect is assumed to be supported. The insect is stable when at least 4 legs are in the "1" state. Additionally, we define six stable configurations with 3 legs.

A gait is defined in terms of a propagation of the cellular automaton. Most of the propagations are inherently periodic (limit cycles).

Experiments

Experiment 1

In this experiment we applied a genetic algorithm to a population of non-uniform cellular automata. We consider fixed initial conditions in which all the legs are in their power stroke.

We use a generational genetic algorithm with linear scaling but without elitism (Goldberg 1989) . These considerations provide the opportunity to obtain several different solutions to the problem in the same run.

Genome representation The representation of the genome consists of the concatenation of the values of the state transition function of each cell using the order imposed by the state transition table. For example, consider the transition function shown in table 2.

The right column of the state transition function is codified in the genome using the order imposed by the table. In this way, values are indexed in the genome and can be accessed directly. Concatenating the values

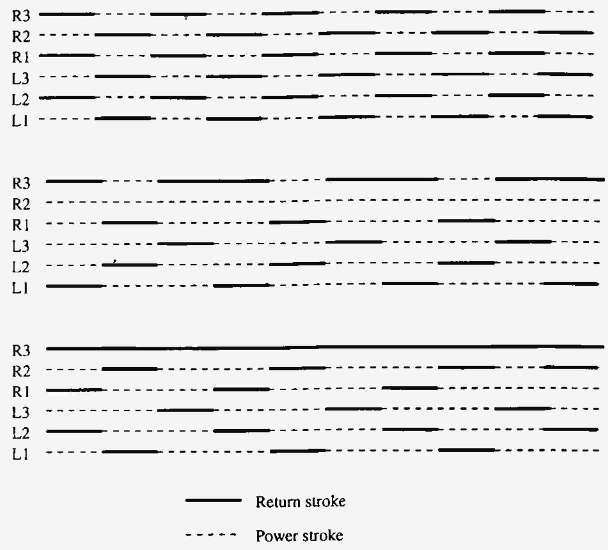

Figure 3: Experiment 1: gaits

for all cells yields a genome of length 64.

$$\overbrace{\underbrace{11010001}_{L_1}\underbrace{1\cdots\cdots1}_{L_2}\underbrace{1\cdots0}_{L_3}\underbrace{0\cdots1}_{R_1}\underbrace{1\cdots\cdots1}_{R_2}\underbrace{1\cdots0}_{R_3}}^{\text{64 bits}}$$

Fitness function Fitness is defined as the distance traveled by the insect as long as it remains stable. We assume that the insect takes one step if it is stable and if at least one return stroke is immediately followed by a power stroke.

Locomotion behavior is inherently periodic. This observation indicates that the evaluation of individuals can reach an infinite loop. To avoid this problem, we define a maximum distance traveled by the insect.

Parameters of the runs We use a population of 256 individuals, and a maximum of 100 generations. We set the crossover and mutation probabilities to $p_c = 0.6$ and $p_m = 0.001$, respectively. Also, we set the maximum distance traveled by the insect to 64 steps.

Results We performed several runs with this model. In each run, the evolutionary process yielded individuals capable of sustained movement. The gaits obtained are similar to gaits observed in insects, including those resulting from amputation. Figure 3 shows some of the gaits obtained from this experiment.

The first gait corresponds to the tripod gait. In the second gait, the cell R_2 converges to the power stroke. This is interpreted as a lesion in which the leg drags. In the third gait, the cell R_3 converges to the return stroke. This is interpreted as an amputation of the leg.

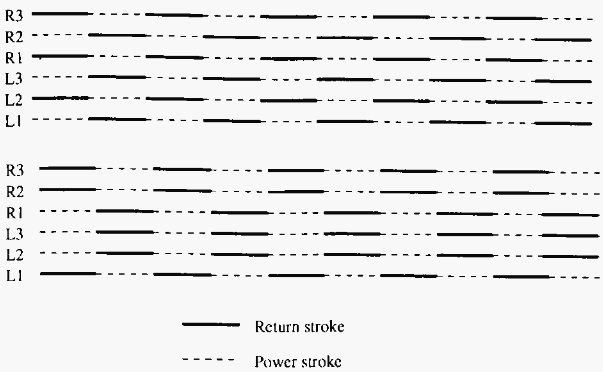

Figure 4: Experiment 2: periodic attractors

State	Phase
1	power stroke
2	power stroke
3	power stroke
0	return stroke

Table 3: States of the leg

State	Protraction	Retraction
1	0	2
2	0	3
3	0	3
0	0	1

Table 4: State transitions

Experiment 2

In this experiment we explore the generality of the solutions found in our experiments. The genetic algorithm searched for a non-uniform cellular automaton capable of producing a sustained movement from all valid initial conditions. We considered all the 28 configurations in which the insect is assumed to be supported.

We used the genetic algorithm of experiment 1.

Results. We performed several runs with this model. In each run, the evolutionary process yielded individuals capable of sustained movement. The gaits obtained behave as periodic attractors. From every initial conditions, the cellular automata converge to a particular gait. Two of the periodic attractor obtained are shown in figure 4.

In most cases, the periodic attractors obtained correspond to different versions of the tripod gait and all of the initial conditions converge to the same gait. In other cases, some of the initial conditions converge to a tripod gait and the rest converge to a different tripod gait. These results show the existence of several periodic attractors that separates the state space into different basins of attraction sets.

Experiment 3

The model considered in previous experiments is incapable of producing several gaits observed in insects. This problem arises because the model captures the approximation to the extreme positions in a limited way. A solution to this problem is to extend the neighborhood of each cell. However, with this modification the distributed nature of the model will be affected.

Another solution to this problem is to extend the state space of each cell. We present a modification of the model in which the power stroke is split into 3 states. These states represent different advance degrees of the leg. Invariably, the return stroke is assumed to reach the anterior extreme position in one time step. With this modification, each leg may assume four different states as shown in table 3.

Our model is restricted to forward walking. This consideration constrains the transitions between states of each leg. These constrains, in turn, provide the possibility of reducing the range of the state transition function of each cell. In consequence, we consider 2 possible values "0" and "1" corresponding to the actions of protraction and retraction. The indicated action returned by the state transition function is used to update the state of each leg as indicated in table 4.

Genome representation The genome representation for this model is essentially the same as in previous experiments. However, due to the extension of the state space of the cellular automata, the length of the genome increases to 768.

$$\overbrace{\underbrace{1\cdots1}_{L_1}\underbrace{1\cdots\cdots1}_{L_2}\underbrace{1\cdots0}_{L_3}\underbrace{0\cdots1}_{R_1}\underbrace{1\cdots\cdots1}_{R_2}\underbrace{1\cdots0}_{R_3}}^{768\text{ bits}}$$

Fitness function. Fitness is defined as the distance traveled by the insect as long as it remains stable. We assume that the insect takes one step if it is stable and if at least one protraction movement is immediately followed by a retraction movement or if at least three retraction movements are executed by legs that are in states 1 or 2.

Parameters of the runs. We use a population of 2048 individuals, and a maximum of 100 generations. We set the crossover and mutation probabilities to $p_c = 0.6$ and $p_m = 0.001$, respectively. Also, we set the maximum distance traveled by the artificial insect to 64 steps.

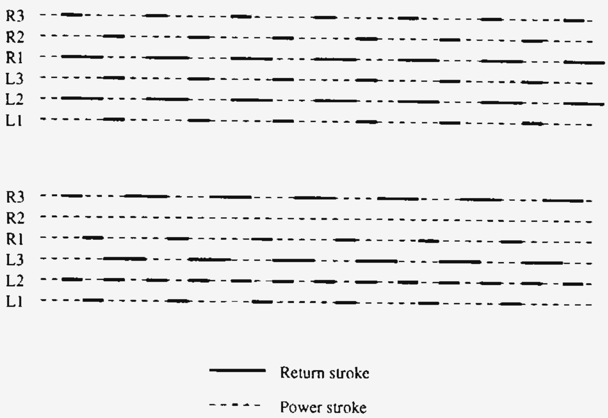

Figure 5: Experiment 3: gaits

Results. We performed several runs with this model. In each run, the evolutionary process yielded individuals capable of sustained movement. The gaits obtained in this experiment exhibit more complex periodic behaviors. Two of the gaits obtained with this experiment are shown in figure 5.

Conclusions and Future Work

Cellular automata are recognized as simple, general and explanatory models for a wide variety of emergent collective phenomena. We propose the application of cellular automata to the synthesis of agent behaviors.

Depending on the research goals, cellular automata can be very useful models when modeling agents. Agent behaviors can be coded in a simple, parsimonious form. Additionally, the behavior produced by cellular automata can be analysed using the formal framework of the theory of dynamical systems.

In this work, we demostrate the application of cellular automata to the synthesis of locomotion behavior on a simulated insect. We use an evolutionary process to shape the dynamical law of the system. The model was capable of evolving several commonly observed gaits in insects.

When we explore the generality of the solutions, the evolutionary process yielded periodic attractors which are invariant from the initial conditions. The indentification of attractors and their corresponding basins of attraction sets can be very important when modeling agents for which the conditions of the environment are uncertain. These behaviors are invariant to perturbations.

The focus of this study has been the evolution of locomotion behavior. An immediate extension of this work is the consideration of other agent behaviors. Other extensions include a more formal analysis of the behavior of the system using tools provided by the theory of dynamical systems, such as the identification of separatrices of the state space in the presence of several periodic attractors. These studies will provide a framework for understanding the emergent and dynamical properties of agent behaviors.

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