A Species-based Approach to Brain-Body Co-Evolution of Modular Robots

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ABSTRACT
Compared with fixed morphology robotic systems, self-reconfigurable modular (SRM) robots can reconfigure themselves to form a variety of morphologies, and carry on various types of motions. Recently, some co-evolutionary approaches have been proposed to co-evolve the robot morphology and associated controller simultaneously for locomotion tasks. However, these co-evolution approaches don't consider some physical limitations of SRM robots and usually request longer evolution process due to extensive searching space. To address these issues, we proposed a species-based co-evolution (S-CoE) algorithm. The S-CoE algorithm is applied on a simulated modular robot system and evaluated under two testing scenarios.

Categories and Subject Descriptors
I.2.9 [Computing Methodologies]: Artificial Intelligence—Robotics

Keywords
Evolutionary Robotics, Self-Reconfigurable Modular Robots, Brain-Body Co-Evolution.

1. INTRODUCTION
Compared with fixed morphology robotic systems, self-reconfigurable modular (SRM) robots can reconfigure themselves to form a variety of morphologies. Currently various SRM robots have been developed. The major limitation of the current state-of-the-art SRM robotic system is that the human users have to explicitly predefine target structures and motion controllers of SRM robots. This process could be tedious and heavily rely on users' design experiences. To make this process more efficient and autonomous, evolutionary approaches have been proposed to reconfigure the structures and controllers of SRM robots [1]. Furthermore, some approaches have been proposed to co-evolve the morphology and controller of robotic systems simultaneously in [2-4]. However, most existing co-evolution algorithms have taken little considerations on some physical limitations of SRM robots, such as module's limited connection capacity, and fixed number of total modules in the system. In addition, as the number of the robot modules increases, the searching space of morphology and controller increases drastically. In this paper, we introduced a new co-evolution approach to address these challenges, called species-based co-evolution (S-CoE) approach. By using building blocks and species, the major contribution of S-CoE is that the co-evolutionary process is expedited significantly by focusing on those important parts to be evolved.

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2. THE METHOD
2.1 Representation Models
To provide more flexibility on morphology transformation, we proposed a new SRM robotic system called Cross-Ball in [5]. Basically a robot module is a ball with an arm system. The body of the module has 6 stationary attachments in orthogonal directions so a module can be locked with 6 neighbors. The arm system has two degrees of freedom: rolling and pitching. First, we propose a tree-based method for morphology representation based on *building blocks*. Building blocks are atoms of a morphology, and each building block may consist of multiple robot modules which are grouped together in a specified manner. Currently, building blocks are predefined before the co-evolution process starts. Target morphology can be described by a tree structure of building blocks. Each building block is a node of the tree. The connection relationships among modules are edges of the tree. Then, we adopt the continuous time recurrent boolean neural network (CTRNN) [6] as the controller representation for SMRs, which is defined as $\tau_i \dot{y}_i = -y_i + \sum_{j=1}^{n} w_{ij}\sigma(y_j)$, where τ_i is the internal time constant of neuron *i*. y_i is the activation level of neuron *i*. w_{ij} is the connection weight from neuron *j* to neuron *i*. $\sigma(x)$ is a sigmoid function. The bi-directional connections between neurons can have weight as 1, -1 or 0. At each time step, the activation level y_i is readjusted by the sign function. Two nodes are assigned to each module so that it can control two degrees of freedom of each module's dynamic joints. Therefore, given *N* modules, the controller is composed of a network with *2N* nodes. At each time step, the activation level of two neurons x_{i1} and x_{i2} of module *i* will affect the module's behavior in the follow four cases: (1) if x_{i1} >0 and x_{i2} >0, the arm roll 15° and pitch 15°; (2) if x_{i1} >0 and x_{i2} <0, the arm roll 15° and pitch -15°; if x_{i1} <0 and x_{i2} >0, the arm roll -15° and pitch 15°; if x_{i1} <0 and x_{i2} <0, the arm roll -15° and pitch -15°.

2.2 Co-Evolutionary Process

Given the total number of modules and predefined *building blocks*, all possible combination of building blocks can be easily enumerated. We call this kind of combination as the *species*. For each species, these building blocks can be combined in different ways to generate various morphologies, called *individuals*. To improve the searching efficiency of co-evolutionary process, a species-based co-evolution (S-CoE) algorithm is proposed to efficiently utilize building blocks and species for robot morphology reconfiguration. The objective of the S-CoE is to first discover appropriate species and then focus on those selected species with better fitness values to generate better individuals more efficiently. In short this S-CoE has the following steps. (1) Enumerate species based on building block types and total amount of modules, where each species randomly generates equal amount of individuals. (2) Evaluate all individuals. (3) Each species adjusts the number of generated children based on: $M_i^{t+1} = Fitness_i^t / \sum_{n=1}^{k} Fitness_n^t$, where M_i^{t+1} is reproduction value of species i at generation t+1. $Fitness_n^t$ is the best child from species i at generation t. (4) Each species reproduces its own children by using the roulette-wheel selection, where the morphology operation is crossover (switch two building blocks and the all their children) and controller operator is mutation (randomly mutate 5% of connection weights of neuron networks). Then the system goes back to Step 2 until the max generation threshold is hit.

3. EXPERIMENTAL RESULTS

The S-CoE algorithm have been verified in the simulated Cross-Ball systems on two case studies, where physical constraints (i.e., connection constraints) of the Cross-Ball have been taken into considerations in the PhysX engine based simulator. As shown in Fig. 1, the first case study is to generate a SRM robot which can escape from a jail with some low fences, and the second case is to generate a SRM robot which can carry locomotion in an open space. The fitness value is defined as the moving distance of the SRM robot from the mass center after certain iteration of the CTRNN controller update and motor movements. The system parameters are: the number of modules is 10, building block types include single and arm, number of children is 10, and maximum number of generation of evolution is 20. Species are listed in Table 1. For the comparison purpose, we also implemented a vanilla co-evolution algorithm, which is similar to the proposed hierarchical co-evolution algorithm, but it doesn't have the building blocks and inner species competition.

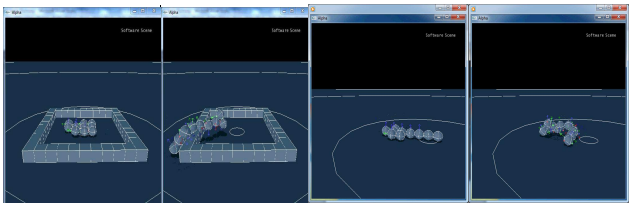

Figure 1. Two case studies: jail break and open space.

Each case has conducted for 4 runs. Fig. 2 and 3 compare the achieved best performance using the S-CoE and the vanilla co-evolution algorithm. Obviously the former one significantly outperforms the other one on locomotion performance because it can generate morphology and motion controller solution more efficiently.

Table 1. The number of building blocks in each species

	Species 1	Species 2	Species 3
# of Single Building Block	10	6	2
# of Arm Building Block	0	1	2

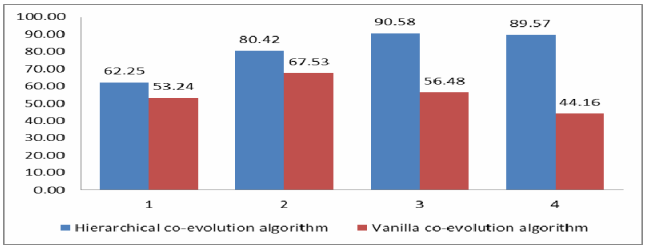

Figure 2. The performance of the hierarchical and vanilla co-evolution algorithm on jail break experiment.

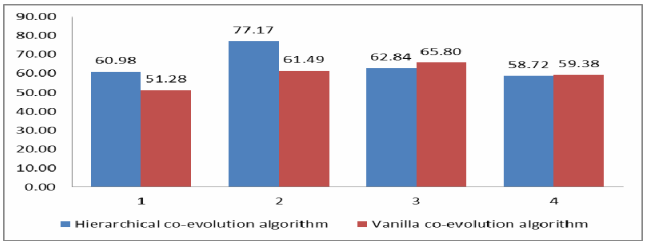

Figure 3. The locomotion performance comparison of the hierarchical and vanilla co-evolution algorithms in a 2D open space.

4. CONCLUSION

In this paper, we proposed a S-CoE algorithm to discover efficient morphology and motion controller for SRM robotic systems simultaneously. The S-CoE algorithm has been verified on two case studies in a physics-engine based simulation. The experimental results have demonstrated the feasibility and efficiency of S-CoE on Cross-Ball SRM with physical constraints. In the future, we will develop new approaches to automatically discover valuable building blocks for SRM robots.

5. REFERENCES

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