Evolutionary Hexapod Robot Gait Control Using A New Recurrent Neural Network Learned Through Group-based Hybrid Metaheuristic Algorithm

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ABSTRACT

This paper proposes a new recurrent neural network (RNN) structure evolved to control the gait of a hexapod robot for fast forward walking. In this evolutionary robot, the gait control problem is formulated as an optimization problem with the objective of a fast forward walking speed and a small deviation in the forward walking direction. Evolutionary optimization of the RNNs through a group-based hybrid metaheuristic algorithm is proposed to find the optimal RNN controller. Preliminary simulation results with comparisons show the advantage of the proposed approach[1].

CCS CONCEPTS

• **Computing methodologies** → Artificial intelligence; Machine learning • **Theory of computation** → Design and analysis of algorithms

KEYWORDS

Particle swarm optimization, genetic algorithms, evolutionary robots, hexapod robots

1 INTRODUCTION

In evolutionary robots, the skill of a robot is learned through interactions with environments [1]. For legged-robots, locomotion control is an important task. One popular approach to accomplishing this task is the generation of rhythmic patterns using a central pattern generator (CPG) [2]. The use of different structures of recurrent neural networks (RNNs) as CPGs for biped [3,4] and hexapod robots [5,6] gait control has been studied. For hexapod robots, the control of a single leg using a Fully Connected RNN (FCRNN) and the connection of multiple, identical FCRNNs (MFCRNN) to coordinate the six legs of the robot for forward walking have been proposed [5,6]. In contrast to the MFCRNN, this paper proposes a sinusoidal-activated MFCRNN (S-MFCRNN) that consists of a smaller number of nodes and connection weights for gait control.

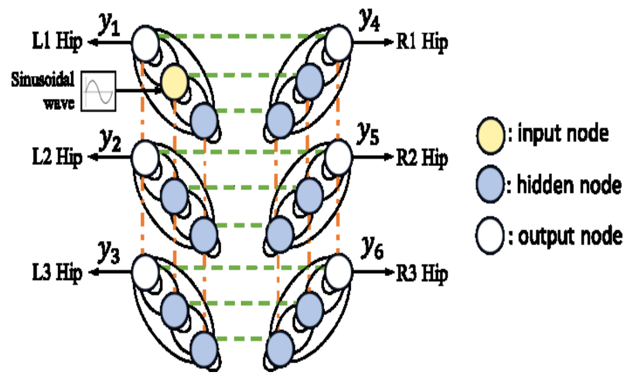

Figure 1: The S-MFCRNN controller architecture.

Optimization of the weights in the MFCRNN through GAs [5] and symbiotic species-based particle swarm optimization (SSPSO) [6] has been proposed. In contrast to optimization using GA or PSO, the hybrid of GA and PSO has been proposed in several studies [7-9]. Among these hybrid optimization algorithms is the evolutionary group-based particle swarm optimization (EGPSO) [9]. The superiority of EGPSO over various PSO and GAs in optimizing fuzzy systems motivates the application of EGPSO to the S-MFCRNN-based hexapod robot gait generation problem in this paper.

The remainder of this paper is structured as follows. Section 2 introduces the S-MFCRNN architecture and its application to the hexapod robot gait control using the EGPSO. Section 3 presents simulations. Finally, Section 4 presents the conclusions. .

2 EVOLUTIONARY GAIT CONTROL

2.1 S-MFCRNN for Feedforward Gait Control

Each leg in the hexapod robot consists of two motors, with one moving the foot up or down and the other driving the leg to swing forward or backward. Fig. 1 shows the architecture of the S-MFCRNN. The state of node i is described by

$$\tau \dot{y}_i = -y_i + a\left(\sum_j w_{ij} y_j - b_i\right) + x_i \qquad (1)$$

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where x_i and y_i are the input and output of node i, respectively. The relaxation time scale τ, bias b_i, and feedback w_{ij} in (1) are all optimized using the EGPSO. The activation function a is a bipolar sigmoid function. Each FCRNN consists of three nodes and nine feedback weights, the network size of which is smaller than the five-node (25 weights) FCRNN in the MFCRNN [5, 6]. The FCRNN is designed as a single leg controller. The six FCRNNs in Fig. 1 share the same nine connection weights. The dashed and dash-dot lines in Fig. 1 represent cross body and intersegmental connections of neighboring FCRNNs, respectively. Based on the gait symmetry property, the intersegmental connections along each side of the body are set to be identical. Likewise, the cross body connections between the front, middle, and back leg controllers are identical. Therefore, there are only three body and three intersegmental connection weights that have to be optimized by the EGPSO. A sinusoidal input is applied to the FCRNN in the left-front (L1) leg to help generate rhythmic patterns for leg control. The output y_i of an FCRNN controls the forward ($y_i > 0$) and backward ($y_i < 0$) swings of a leg. A foot moves down one step ahead before the leg starts to swing backward and moves up when the leg starts to swing forward.

2.2 Evolutionary Control Through EGPSO

The purpose of hexapod robot gait controller optimization is to find an optimal S-MFCRNN to control the robot to walk as fast and straight as possible. The EGPSO consists of a population of solutions, with each solution optimizing the parameters in (1) and the weights in the S-MFCRNN. In performance evaluation, an S-MFCRNN is applied to control the robot in a simulation environment using the Webots robot simulator. After a given number of control time steps, the walking performance of each solution is evaluated by a cost function. The cost values of all solutions are involved with creating new solutions in the optimization process of EGPSO. New solutions in the EGPSO are created partially by group-based GA and partially by group-based PSO. Details of the EGPSO can be found in [9].

$$f = f_1 + \left[\exp\left(\frac{f_2}{w_b}\right) - 1\right] \tag{2}$$

where the normalization coefficient w_b is the width of the robot body. The first term $f_1 = y_{goal} - y_{robot}$ measures the forward walking distance. The second term f_2 measures the average deviation over n_s swing states and is give as follows:

$$f_2 = \frac{\sum_{i=1}^{n_s} x_i}{n_s} \tag{3}$$

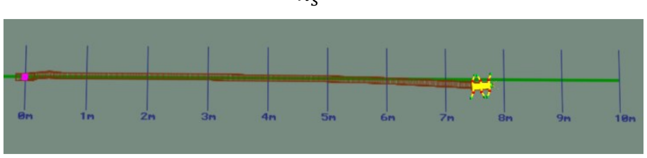

Figure 2: The trajectory of the hexapod robot controlled by an EGPSO-designed S-MFCRNN.

3 SIMULATION RESULTS

In the EGPSO, the swarm size and iteration number were set to 50 and 1000, respectively. The control time step was 320 with the duration of each time step set to 64 ms. A total of 30 runs were performed. The average cost value was 6.1, where the average walking distance in the y-axis was 4.56 m. Fig. 2 shows the walking trajectory of the robot, where the patterns are rhythmic in controlling the swings of the leg. The model size of the simulated robot was smaller than that in [6]. For comparison, the learning method and cost value in [6] was applied to control the robot in this paper. The average walking distance was 2.90 m. The result shows the proposed evolutionary control approach generates the gait with a longer walking distance in the forward direction than that in [6].

4 CONCLUSIONS

The preliminary simulation result shows the proposed evolutionary S-MFCRNN-based control approach is effective in generating the walking gait of a hexapod robot for forward walking. In the future, the patterns of the gait will be analyzed and implemented in a real robot.

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