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Evolution of Herding Behavior of Multiple Autonomous Mobile Robots

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Abstract

We study the evolution of herding behavior of multiple autonomous mobile robotic agents. Agents are cloned to form a homogeneous team. Cooperation strategies for a team of the robots are represented in a neural network. An evolutionary algorithm is used to evolve the neural network fitted for herding behavior. The effectiveness of the method is experimentally tested in a simulated environment for solving a furniture transportation problem.

1 Introduction

Some tasks can be done faster or more easily by dividing it up among many agents. Other tasks may not only be solved better by using multiple agents, but can only be effectively solved, by using teams of agents working together. The global behavior of the group of mobile robots is determined by the local interactions.

The problem of cooperation and communication between multiple mobile agents has recently been studied by many researchers studying artificial life and evolutionary computation.

Reynolds [Reynolds, 1993] used genetic programming to evolve "critters" which reacted with a herd instinct to outside preditors. He evolved a single controller which moved each critter based on its position and information about its neighbors and predators. Each critter used this same controller algorithms to make movement decisions. Haynes *et al.* proposed a genetic programming method to generate a team by considering the whole team as one individual [Haynes *et al.*, 1995]. They considered the subtrees of a genetic program as subindividuals within a main individual, each of which may serve a distinct specialized purpose. Luke and Spector implemented heterogeneous breeding strategies which is functionally very similar to the clear method of producing homogeneous individuals [Luke and Spector, 1996]. In both cases standard genetic programs are grown, and only one "individual" is tested at a given time. For homogeneous teams, individuals are tested by cloning them to form teams. and the resulting teams are tested in the environment. Heterogeneous teams, however, are formed from the individual's collection of subtrees.

We have designed a self-organizing chaotic neural network for the evolution of robot herding behavior. Robots are cloned to form a homogeneous team. Cooperation strategies for a team of the robots are represented in the neural network. Evolutionary algorithms are used to evolve the neural network fitted for herding behavior. The effectiveness of the method is experimentally demonstrated on a furniture transportation problem.

The fitness of each network is evaluated by implanting it into the robots. Each robot is given a bucket of points at the outset. The robots are allowed to move a fixed maximum number of steps. At each movement, the badness of their behavior is evaluated and penalized. When it collides, for example, with its colleagues, it gets K_{coll} points subtracted from the bucket. An amount of K_{away} points is also subtracted when it moves too far away from its colleagues. This factor encourages herding behavior. When the table is out of sight of the robot on each move action, the robot gets K_{sight} points decreased. To encourage the movements of the robots, we also penalized the robots that stay at the same location or move seldom.

The paper is organized as follows. Section 2 motivates the approach and describes the method for evolving herding behaviors. Section 3 presents the neural net architecture. Section 4 provides experimental results.

2 Evolving Cooperative Agents

Some tasks, such as transporting a large table, requires multiple robots to cooperate. To study cooperation strategies in such a context, we constructed a virtual workspace of the robot on a plane of 20m × 20m. Figure 1 shows the workspace occupied by the table and robots to transport it. We assume cylinder robots of 20cm in diameter. It has four sensors positioned 45 degree upward. One move action of the robot brings its body 5cm to the direction it heads at the time. The sight of robots is limited to 2m. An additional sensor detects the target object within 10m. Sensors are connected to the input nodes of a neural network that determines the effector values for move actions. The initial environment contains three obstacles which are located randomly between the robots and the table.

The sensory inputs needed to control the robots include the pressure for measuring the unbalance of weight of the table among the member robots, the detectors for the table and obstacles, a communication signal for synchronization of group behavior, and a stagnation detector for the determination of the direction to move to. The outputs for motor control include the values for driving the left/right motors of the wheels and the signal to send for communication necessary for finding and lifting the table.

In the simulations described below, we have used as input to the network the detectors for the table to transport, colleagues, and obstacles. The network has 9 output units, 8 for determining the direction and the rest for non-moving.

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$$\begin{aligned} A &= K_{away} \cdot \text{NumAways} \\ &\quad + K_{coll} \cdot \text{NumCollisions} \\ &\quad + K_{sight} \cdot \text{NumOutsights} \end{aligned} \tag{1}$$

where NumAways is a count for the number of being far away from the colleagues, and NumCollisions and NumOutsights are counts for collisions and being too far away from the table.

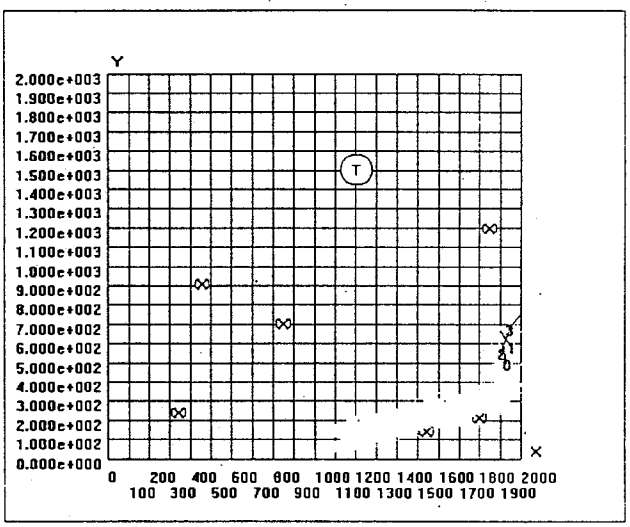

Figure 1: The simulation environment.

To encourage the movements of the robots, the resulting bucket of points is multiplied by the following factor

$$S = K_S \cdot \text{NumStepsMoved} \tag{2}$$

where K_S is a constant amd NumStepsMoved is the total number of steps moved. This term penalizes the robots that stay at the same location or move seldom.

The bucket of remaining points is subtracted again by a fractional amount of the distance from the table:

$$D = K_D \cdot \text{FinalDisplacement} \tag{3}$$

where K_D is a constant. This is to promote moving toward the table.

Overall, the fitness of a robot or its neural network is:

$$F_i = (\text{Bucket} - A) \times S - D \tag{4}$$

where A, S, and D are defined as above.

After being evaluated their fitness, the individuals are selected to be parents for recombination. The selection probability of each individual is given as:

$$R_i = \frac{F_i - F_{min}}{F_{max} - F_{min}} \tag{5}$$

where F_{max} and F_{min} are, respectively, the maximum and minimum fitness values of the individuals in the current population. We used steady-state selection, i.e. 5% of the population are replaced after each evaluation. Thus the population evolves more slowly but continuously than in generational selection.

3 A Neural Net for Herding

The neural network consists of four layers (Figure 2). The bottom layer is the input layer that receives sensory inputs. The next three layers are the recurrent neural network (RNN) layer, the self-organizing map (SOM) layer, and the Cognitron output layer.

The recurrent neural network receives the environmental inputs and processes them to detect the spatio-temporal pattern of the inputs. It contains both excitatory and inhibitory neurons. The recurrent network used in the experiments contains 84 neurons in a virtual cylinder. The neurons are connected with other neurons in the neighborhood more frequently than the neurons in the distant area within the cylinder. We adopted a neuron model with chaotic dynamics [Adachi and Aihara, 1997]. The activation is determined by:

$$x_i(t+1) = f\left[\sum_{j=1}^{M} v_{ij} \sum_{d=0}^{t} k_e^d A_j(t-d) + \sum_{j=1}^{N} w_{ij} \sum_{d=0}^{t} k_f^d x_j(t-d) - \alpha \sum_{d=0}^{t} k_r^d g\{x_i(t-d)\} - \Theta_i\right] \quad (6)$$

where v_{ij} and w_{ij} are synaptic weights to the ith constituent neuron from the jth external input and from the jth constituent neuron, respectively, and k_e, k_f, and k_r are the decay parameters for the external inputs, the feedback inputs, and the refractoriness, respectively. We set $k_e = k_f = k_r$ and $g\{x_i(t-d)\} = x_i(t-d)$. The recurrent network considers the spatio-temporal summation of both external inputs and feedback inputs from other chaotic neurons.

The neurons in the recurrent network learn their weights for each input data. The modified Hebbian learning rule is used to adapt the weights:

$$w_{ij}(t+1) = w_{ij}(t) + r\{1 - w_{ij}(t)\}h\{x_i(t), x_j(t)\} - K\{w_{ij}(t)\} \quad (7)$$

where $K\{w_{ij}(t)\}$ is the weight decay function. The parameters are determined by an evolutionary method. For each input data, the network is activated iteratively to converge to a pattern or oscillate between two or more patterns. For our application, it is useful if the network produces similar output patterns for similar input patterns.

The next layer is the self-organizing map (SOM). Its objective is to recognize the activation pattern of the recurrent network and classify it into a class. The SOM learns for every update of activation at the recurrent network layer:

$$w_{ij}(t+1) = w_{ij}(t) + r_{SOM}\{a_j - w_{ij}(t)\} \quad (8)$$

This implies that the SOM layer learns to recognize the activation patterns of the recurrent network. If the RNN converges to a single pattern, then SOM recognizes it. The ultimate winner of the SOM is the unit whose weight vector has the smallest distance to one of the activation patterns at RNN.

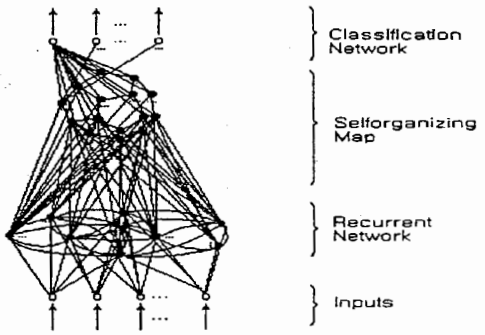

Figure 2: The multinet neural architecture.

The output layer determines the output of the network based on the winner of the SOM network. This layer is trained using reinforcement learning as follows:

$$y(s) = \begin{cases} w_{cij}(t) + r_c\{1 - w_{cij}(t)\} \cdot s \cdot a_j & \text{if } s \geq 0 \\ w_{cij}(t) + r_c \cdot w_{cij}(t) \cdot s \cdot a_j & \text{otherwise} \end{cases}$$

where $s, -1 \leq s \leq 1$, is the normalized difference between the present penalty and the previous one. a_j is the activation value of the winner at the SOM layer.

4 Experimental Results

Figure 3 plots the evolution of fitness values as generation goes on. The thick line is the average fitness of the population and the thin line is the fitness of the best individual at each generation. It can be clearly observed that the average fitness of the robotic agents increases as they evolve in the environment. The best-of-run individual was evolved after 30 generations. After 55 generations the fitness of the best-of-generation individual did not change. The fluctuations in the best fitness reflects the fact that we did not apply the elitist selection strategy.

Though not shown here, we also observed tendency of a convergence of winners at the SOM layer as the

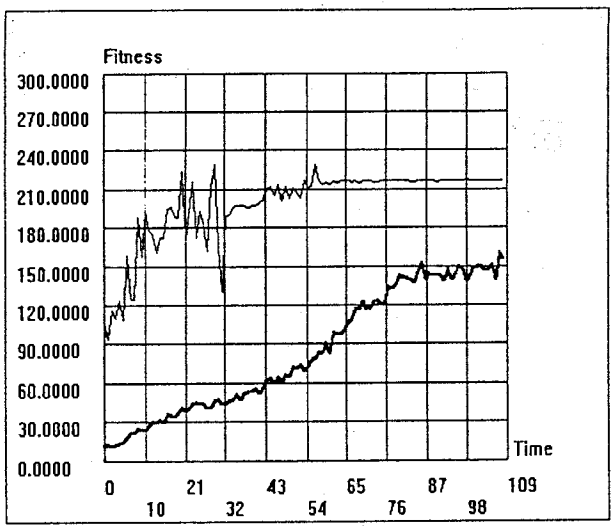

Figure 3: Change of the best and average fitness values.

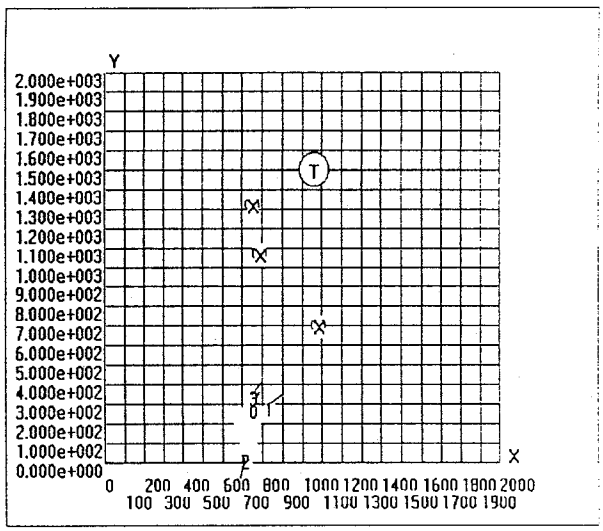

Figure 4: The robots herding to the table.

recurrent neural network updates its activation. Figure 4 shows the behavior of robots controlled by the neural network by the evolutionary algorithm. As generation goes on, improvement in robots' herding behavior was observed in comparison to the behavior of the robots at early generations.

5 Concluding Remarks

We have described a method for evolving herding behavior of a group of small mobile robots. A neural network architecture is presented that processes spatio-temporal patterns of input stimuli, detects convergent patterns, and produces motor outputs corresponding to the stimuli pattern. The network is evolved by situating the robots in the simulated world and rewarding positive actions and penalizing negative actions by a carefully designed fitness function. The performance was demonstrated in the context of a table-transport problem. Future work should refine and improve the current framework. We are studying other efficient learning strategies that assign credits to the component networks to evolve more goal-directed collective behavior.

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