Evolution of Altruism: Spatial Dispersion and Consumption Strategies

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ABSTRACT

The work presented here is concerned with the evolution of altruistic behaviour in a population of agents subject to an open-ended evolutionary process. In this context, it is well known that genotypic relatedness plays a key role with respect to the level of altruism that can be observed. Such relatedness may be enforced through particular selection mechanism (e.g. kin-recognition) as well as particular dispersion strategies (e.g. low dispersion favours local interactions). This paper presents results on the importance of the evolution of particular dispersion strategies whenever consumption strategies are enforced. A key result from this paper is that whenever altruism is difficult to display when consuming food (i.e. being unable to share while eating), higher dispersion behaviour are evolved, which is a counter-intuitive result at first sight.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence

Keywords

Evolution of Altruism, Embodied Evolution, Evolutionary Adaptation, Tragedy of Commons

1. INTRODUCTION

Altruism can be observed whenever a specific individual in a population deliberately sacrifices part of its own fitness in order to increase the fitness of other individuals [4]. Several theories have been proposed to explain this type of behaviour and its particular properties with respect to other kind of cooperative behaviours [6]. The well-accepted theory of inclusive fitness, as proposed in [3, 5] hypothesises the importance of genotypic relatedness as a key element to explain self-sacrifice.

In this paper, we are interested in a particular mechanism that can act on the altruistic level displayed within a population: the evolution of spatial dispersion. Indeed, spatial behaviours can act indirectly on the level of genotypic relatedness, and may be considered as favouring higher levels of altruism whenever dispersion is low (i.e. leading to local interactions). However, there is a trade-off between favouring such local interactions and the ability to gather food in the environment.

The rest of the paper investigates such a trade-off, where consumption behaviour and dispersion behaviour are considered. In particular, counter-intuitive results are presented, where dispersion is increased rather than decreased whenever food consumption makes it difficult to share, which is expected to weaken altruism. That is the evolution of dispersion behaviours does not always compensate for selfish or altruistic consumption behaviour, as one may have hypothesised.

2. EXPERIMENTAL SETUP

The setup used in this work features simulated robotic agents (equipped with limited batteries) which must harvest energy from the environment in order to maintain their integrity. Each robotic agent consumes a fixed amount of energy at each iteration. Food items are randomly placed in the environment. Once a food item has been harvested it becomes unavailable for a defined time named regrow delay, linearly proportional to the energy consumed.

Open-ended Evolutionary Algorithm

The **mEDEA** algorithm was initially introduced in [1]. It performs as an evolutionary adaptation algorithm that can be distributed over a population of robotic agents and is solely driven by environmental pressure (rather an explicit fitness function). In this setup, each agent may interact only with neighbouring agents. At the end of pre-determined lifetime, a random selection is performed among the genomes gathered from other agents, and a gaussian mutation is applied. As a results, a particular genome is successful only if it manages to both avoids the pitfalls of the environment and maximizes the number of encounters with other agents. Please refer to [2] for a full description.

Measure of Spatial Dispersion

In order to characterize an agent's behaviour, its dispersion is monitored by counting the number of locations visited. To do so, the environment is divided into a grid of cells. At the end of a generation, an approximation of the area covered by an agent is computed thanks to Equation 1 (the equation is applied only on the grid of the concerned agent).

$$AreaCovered = \frac{\#VisitedCells}{\#Cells * lifetime} \tag{1}$$

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Modification of Consumption Strategies

It has been show that altruistic behaviours are linked to strong genotypic relatedness. This relatedness can be enforced by low spatial dispersion. In this paper we are investigating how different spatial dispersion strategies are evolved with regards to enforced consumption strategies.

An agent's consumption strategy corresponds to the energy taken from energy point. In this work a consumption strategy is determined by the cost paid by agents (i.e. the energy not consumed from an energy point).

The energy taken by agents is computed from the cost imposed to them by Equation 2.

$$E_{taken} = max(0, min(EP_{e_{Max}}, r_{E_{max}} - r_{E_{now}}) - Cost) \quad (2)$$

Where $EP_{e_{Max}}$ is the maximal energy in a food item, $r_{E_{max}}$ is the maximal energy level of an agent, $r_{E_{now}}$ is the current energy level of the agent, E_{taken} is the energy consumed by the agent from the food item. If $Cost$ is equal to 0 agents will display a selfish behaviour.

If $Cost$ is equal to $EP_{e_{Max}}$ agents will display a maximally altruist behaviour.

Implementation

A multi-layer perceptron is used to encode the controller of each robot. The input layer is composed of 12 inputs (8 for distance sensors, 1 for the direction to the closest energy point, 1 for the distance to the closest energy point, 1 for the battery level, 1 for the presence of an energy point under the agent), the hidden layer is composed of 5 neurons, and the output layer is composed of three neurons (1 for the rotational speed, 1 for the translational speed, and 1 for the amount of energy consumed). The weights of the MLP are decoded from the active genome of the agent.

3. RESULTS

20 runs are performed in environments where the pressure is low ($EP_{Lag_{Max}} = 25$ *iterations*) until the 400000^{th} iteration. After this threshold, the environmental pressure is increased (by a fix amount of 80 iterations) every 4000 iterations (10 theoretical generations) until the extinction of the population. Two cases are studied: when the cost is fixed to 5 and when the cost is fixed to 40.

In order to compare the behaviours evolved we measure the spatial dispersions of agents when they are placed in the same environment. It features, a cost fixed to 0, a low environmental pressure ($EP_{Lag_{Max}} = 25$ *iterations*), and the absence of genome transmission and selection.

The procedure to measure the spatial dispersion is as follow: 1) Genomes found in one run at iteration 600000 are randomly sampled to create a new population of 100 individuals; 2) This population is embodied in 100 robots; 3) The spatial dispersion is measured during 40000 iterations. This procedure is used 20 times per run. The median results for each cost are presented in Figure 1.

Figure 1 provides counter-intuitive results as it would be expected that an egoistic consumption strategy (cost=5) is compensated by an altruistic dispersion strategy (i.e. lower dispersion). As this is not the case, the reason may be found in the particular setup at hand: the spatial distribution of energy points may enforce a higher dispersion whenever the consumption strategy is egoistic as there are fewer energy

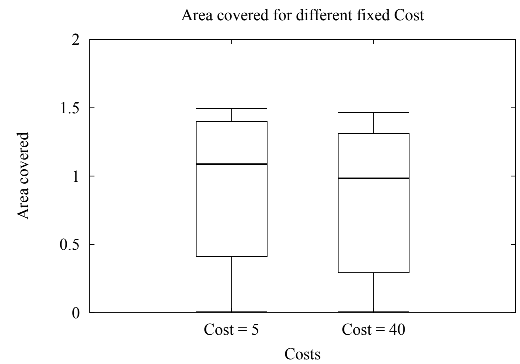

Figure 1: Area coverage for two consumption strategies.

points available at any moment, making the environment more challenging (i.e. it is more difficult to bump into an energy point). Indeed, the number of successful runs with a more altruistic consumption strategy (i.e. cost of 40) is higher than for other consumption strategies. Thus, possibly indicating that enforcing a egoist strategy makes the survival so difficult that it becomes not possible to completely compensate for the egoistic consumption strategy by spatial dispersion.

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