

Generic Behaviour Similarity Measures for Evolutionary Swarm Robotics

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ABSTRACT

Novelty search has shown to be a promising approach for the evolution of controllers for swarms of robots. In existing studies, however, the experimenter had to craft a task-specific behaviour similarity measure. The reliance on hand-crafted similarity measures places an additional burden to the experimenter and introduces a bias in the evolutionary process. In this paper, we propose and compare two generic behaviour similarity measures: *combined state count* and *sampled average state*. The proposed measures are based on the values of sensors and effectors recorded for each individual robot of the swarm. The characterisation of the group-level behaviour is then obtained by combining the sensor-effector values from all the robots. We evaluate the proposed measures in an aggregation task and in a resource sharing task. We show that the generic measures match the performance of task-specific measures in terms of solution quality. Our results indicate that the proposed generic measures operate as effective behaviour similarity measures, and that it is possible to leverage the benefits of novelty search without having to craft task-specific similarity measures.

Categories and Subject Descriptors

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence—*Multiagent systems*

General Terms

Algorithms

Keywords

Evolutionary swarm robotics, novelty search, behaviour characterisation, deception

1. INTRODUCTION

Swarm robotics is a promising approach to collective robotics, where the group-level behaviour emerges from the

local interactions among agents, and from the interactions between the agents and the environment [4]. This approach has the potential to incite several desirable properties in a group of agents, such as robustness, flexibility, and scalability [4]. However, the complexity stemming from the intricate dynamics required to produce self-organised behaviour complicates the hand-design of control systems [21]. Artificial evolution has been shown capable of exploiting the intricate dynamics and synthesise self-organised behaviours (see for example [21, 22, 2, 3]), but the approach engenders several issues. The most prominent issue associated with common evolutionary techniques is *deception* [23]. Deception occurs when the fitness function misguides the search towards local maxima that do not contain adequate solutions to the problem. As the complexity of a problem increases, the fitness landscape typically becomes more rugged and gains more local maxima [19]. As such, it becomes more difficult to craft a fitness function that can successfully guide the search towards the objective [24], i.e., the evolutionary process becomes more vulnerable to deception.

Novelty search [15] is a distinctive evolutionary approach where candidate solutions are rewarded based solely on their behavioural novelty, with respect to previously evaluated solutions. In recent work [7, 8, 9], it was shown that novelty search can avoid deception in the evolution of swarm robotics systems. Besides not being affected by deception, it was also shown that novelty search is able to find a greater diversity of solutions, and the successful solutions were simpler in terms of neural network complexity when compared to those found by fitness-based evolution. But these advantages come at a price: for novelty search to work, it is necessary to craft a behaviour similarity measure, used to compute the novelty of the individuals, specifically for the given task. The results showed that the choice of the novelty metric has a significant impact in the performance of novelty search, and can introduce a significant bias in the evolutionary process.

Previous works have proposed task-independent behaviour similarity measures [10, 6, 18]. These generic measures can potentially be used to overcome the aforementioned limitation of novelty search. Generic measures are typically based exclusively on the sensor and effector values of the agents, and do not rely on task-specific knowledge provided by the experimenter. However, the generic measures described in previous works are aimed at single robot systems.

In this paper, we study how generic measures can be adapted to swarm robotics systems. We propose generic be-

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behaviour similarity measures that use the sensor and effector values of the robots of the swarm to obtain a representation of the typical behaviour of the swarm as whole. The measures are evaluated in two swarm robotics tasks: (i) an aggregation task; and (ii) a task where robots must share an energy recharging station in order to survive. Following previous results [8], novelty search is used in combination with the fitness function, through a linear scalarization of novelty and fitness objectives. NEAT is used as the underlying neuroevolution method.

The results of our experiments suggest that novelty search, when combined with fitness-based evolution, achieves a similar performance with the proposed generic similarity measures and with task-specific similarity measures, regarding the quality of the evolved solutions. We show that the prominent advantages of novelty search, such as its capacity to bootstrap evolution and to circumvent deception [7], are also present with the use of generic measures.

2. RELATED WORK

In this section, we describe the novelty search algorithm, and how novelty search can be combined with fitness-based evolution to improve the effectiveness of the evolutionary process. We move on to discuss the previous applications of novelty search in evolutionary robotics. We conclude with a discussion of the generic behaviour similarity measures proposed in previous works.

2.1 Novelty Search

Novelty search [15] can be implemented over any evolutionary algorithm. The distinctive aspect of novelty search is how the individuals of the population are scored. Instead of being scored according to how well they perform a given task – which is typically measured by a fitness function, the individuals are scored based on their behavioural novelty according to a novelty metric. This metric quantifies how different an individual is from the other, previously evaluated individuals with respect to behaviour.

To measure how far an individual is from others individuals in behaviour space, the novelty metric relies on the average distance of that individual to the k -nearest neighbours, among the current population and a sample of the previously seen behaviours (stored in an archive). Candidates from sparse regions of the behaviour space thus tend to receive higher novelty scores, thereby creating a constant evolutionary pressure towards behavioural innovation.

The behaviour distance between each two individuals is given by a function *dist* that should be provided by the experimenter. The function *dist* is typically defined with domain knowledge. Following this approach, the behaviour of each individual is characterised by a vector of real numbers. The experimenter should design the behaviour characterisation vector so that it captures behaviour features that are considered relevant to the problem or task. The behaviour distance between two individuals is then given as the Euclidian distance between the corresponding behaviour characterisation vectors of the individuals. A distinct approach is to use distance functions that do not rely on any task-specific knowledge. Such an approach is the main focus of this paper and will be detailed in Section 2.2.

2.1.1 Combining Novelty and Fitness

As novelty search is guided by behavioural innovation

alone, its performance can be greatly affected by the size and shape of the behaviour space. In particular, behaviour spaces that are vast or contain dimensions not related with the task can cause novelty search to perform poorly [14, 5], because most of the effort may be spent exploring behaviours that are irrelevant for the goal task. To address this issue, several authors have proposed techniques that combine novelty search with fitness-based evolution [14, 5, 8, 16, 18].

In our experiments, we use a linear scalarization of novelty and fitness objectives [5]. We chose this approach because it can be used together with NEAT without any further modifications, and has shown promising results in previous studies [8]. Linear scalarization of novelty and fitness objectives directs the exploration towards regions of the behaviour space associated with high fitness scores. An individual i is evaluated to measure both fitness, $fit(i)$, and novelty, $nov(i)$, which after being normalised (Eq. 1) are combined according to Eq. 2.

$$\overline{fit}(i) = \frac{fit(i) - fit_{min}}{fit_{max} - fit_{min}}, \quad \overline{nov}(i) = \frac{nov(i) - nov_{min}}{nov_{max} - nov_{min}} \quad (1)$$

$$score(i) = (1 - \rho) \cdot \overline{fit}(i) + \rho \cdot \overline{nov}(i) \quad (2)$$

The parameter ρ controls the relative weight of novelty, and must be specified by the experimenter. fit_{min} and nov_{min} are the lowest fitness and lowest novelty score in the current population, and fit_{max} and nov_{max} are the highest fitness and highest novelty score, respectively.

2.1.2 Novelty Search in Evolutionary Robotics

Novelty search, and other evolutionary techniques based on behavioural diversity, have been applied with success to single robot systems. Some of these applications include body-brain co-evolution [12]; biped robot control [15]; robot navigation in deceptive mazes [15]; sequential light seeking [18]; and a robot ball-collecting task [18]. A comprehensive study of the use of diversity-based techniques in evolutionary robotics is presented in [18].

Gomes et al. [7, 8, 9] showed that novelty search can also provide a valuable contribution evolutionary swarm robotics. In particular, the results showed that the use of novelty search circumvented deception and bootstrapping problems, and could unveil a broad diversity of solutions for a given task. However, the same studies revealed that defining behaviour characterisations for this domain can be a delicate endeavour.

The mapping from behaviour to behaviour characterisation is not injective, and when different behaviours receive the same characterisation, they are said to be *conflated*. Since there are infinitely many behavioural possibilities, many behaviours must be conflated in order to construct a viable search space. Excessive conflation, however, can hinder the evolution of certain types of solutions, and degrade the performance of novelty search. Furthermore, the definition of the behaviour characterisation adds a human bias to the process, which is an aspect that should be minimised in evolutionary robotics [19].

2.2 Generic Novelty Measures

Gomez [10] proposed the use of generic measures for assessing the behaviour similarity between individuals in a single agent task. The proposed approach consists of building state-action trajectories for the agent, i.e., the history of

actions of the agent through time. These trajectories are then compared, obtaining a measure of behaviour similarity, without the need of providing task-specific knowledge. To compare the sequences of actions, the author evaluated the use of Hamming distance, relative entropy, and normalised compression distance (NCD). The experimental setup was based on a discrete box-pushing task, and the results showed that the NCD distance offered the best performance, followed closely by the Hamming distance. NCD is a similarity measure that exploits regularities in the sequences of observations, but introduces a significant computational overhead.

To address the difficulty in designing behaviour characterisations for evolutionary robotics, Doncieux and Mouret [6] proposed and compared generic behaviour similarity measures for evolutionary robotics. Any robotics experiment involves robots with effectors and sensors, whose values reflect the microscopic behaviour of the robot. This notion led to the definition of the following generic measures [6]:

Hamming distance A vector is built with the sensor and effector values of the robot, sampled throughout the simulation:

$$\vartheta = [\{\mathbf{s}(t), \mathbf{e}(t)\}, t \in [0, T]] , \quad (3)$$

where $\mathbf{s}(t)$ and $\mathbf{e}(t)$ are the vectors of the sensor and effector values at time t , respectively, and T is the simulation time. The vector ϑ is then binarised into ϑ_{bin} , by transforming each value to either 0 or 1. The similarity measure is then given as the Hamming distance between the corresponding ϑ_{bin} vectors obtained for each individual.

Discrete fourier transform The ϑ vectors are obtained for each individual, similar to the Hamming distance measure. But instead of using the complete vectors, a Discrete Fourier Transform (DFT) is used to reduce the dimensionality. The similarity measure is defined as the Euclidean distance between the first n_F coefficients of the DFT.

Systematic state count Perception-action states are defined based on the possible combinations of ϑ_{bin} . Relying on the sensor-effector data, the number of times the robot was in a particular state is then evaluated, resulting in a vector of n integers, n being the number of such states. The similarity measure is then defined as the mean element-wise distance between the vectors.

These methods were evaluated in a ball collection task, where the robot had 9 sensors and 3 effectors. The novelty metric was combined with the fitness function through multi-objectivisation. The results showed that the Hamming distance measure was the most effective, being superior to the task-specific similarity measure. The systematic state count and DFT measures displayed a significantly lower performance.

The Hamming distance similarity measure was further tested in [18]. In these experiments, the measure was evaluated in three different tasks (deceptive maze, sequential light seeking, ball-collecting robot) and compared to a number of different diversity maintenance techniques. When using multi-objectivisation of novelty and fitness, the results showed that the generic Hamming distance was at least as good a measure as the task-specific similarity measures, regarding the quality of the evolved solutions.

3. METHODS

3.1 Combined State Count

We propose *Combined State Count* which is an adaptation of *Systematic State Count* (see Section 2.2). Despite the lower performance in the experiments of Doncieux & Mouret [6], when compared to the other generic measures, the concept of this method can be directly adapted to swarms of robots. As such, it is the starting point of our study. The principle is to define states based on the values from the sensors and effectors recorded for each robot. Then, the number of times the robots of the swarm are in each state is computed. There is no discrimination in terms of which robot was in a particular state, i.e, the state counting at the swarm level is the sum of the state counts for each robot in the swarm.

The state counting approach is, however, prone to scalability issues, since the number of states grows exponentially with the number of sensors/effectors, and with the number of possible values for each sensor/effector. To address this issue, we propose modifications over the original *State count*. Scalability is achieved through the use of efficient structures for representing states and characterisations, and mechanisms for reducing the effective number of states.

Efficient State Count Representation

Representing each behaviour characterisation as a vector with one position for each state (as in [6]) can compromise the efficiency of the algorithm if there is a large number of states. However, the number of visited states in one simulation is only a small fraction of the total number of possible states. As such, we can represent each characterisation as a map from states to counts. The counting is normalised according to the size of the swarm, to allow fair comparisons between simulations with different swarm sizes. The behaviour similarity measure is then given by the difference between the state count maps. To calculate the characterisation map m' for each individual, Algorithm 1 is used:

Algorithm 1 State count characterisation

```

 $m \leftarrow \text{Map} < \text{Int}, \text{Float} >$ 
for all simulation-steps do
  for all  $r$  in robots do
     $\vartheta_r \leftarrow \text{read-state}(r)$ 
     $\vartheta'_r \leftarrow \text{discretise}(\vartheta_r)$ 
     $h \leftarrow \text{hash}(\vartheta'_r)$ 
    if  $m$  does not contain  $h$  then
       $m[h] \leftarrow 0$ 
    end if
     $m[h] \leftarrow m[h] + 1/\text{swarmsize}$ 
  end for
end for
 $m' \leftarrow \text{filter}(m)$ 
return  $m'$ 

```

The function *read-state* retrieves the current sensor-effector state ϑ_r for a particular robot r :

$$\vartheta_r = \{\mathbf{s}_r, \mathbf{e}_r\} , \quad (4)$$

where \mathbf{s}_r is the vector of size n_s , composed of the values coming from the n_s sensors of the robot r ; and \mathbf{e}_r is the vector composed of the effector values.

The discretised vector ϑ'_r is obtained by independently normalising each element of ϑ_r to the interval $[0, K - 1]$, followed by an approximation to the nearest integer:

$$\vartheta'_{i,r} = \left\| \frac{\vartheta_{i,r} - \vartheta_{i,\min}}{\vartheta_{i,\max} - \vartheta_{i,\min}} \cdot (K - 1) \right\| , \quad (5)$$

where $\vartheta_{i,\max}$ and $\vartheta_{i,\min}$ are respectively the maximum and minimum values of the i -th sensor/effector, and K is the number of target partitions. The parameter K has direct implications in the number of possible states, and it should be empirically determined. A rule of thumb is to define it accordingly to the length of ϑ . For most applications, K values of 2 and 3 are adequate, categorising the value of each sensor in High/Low, or High/Medium/Low. However, if the robots have a small number of sensors (ϑ is relatively short), higher values of K might be preferred, in order to operate with more detailed behaviour characterisations.

The function *hash* was implemented with the Jenkins' one-at-a-time hash.¹ The intent of hashing the vector ϑ'_r is twofold. First, it allows lookups of the corresponding entry in the m map in $\mathcal{O}(n)$ time, n being the length of ϑ'_r . Second, hashing vectors removes the need of storing ϑ' vectors, which improves the space complexity of the algorithm.

Reducing the Number of States

The function *filter* eliminates the least observed states, in order to improve the efficiency of the algorithm. Preliminary results revealed that robots tend to spend most of their time in a small subset of the state space. Most of the states are visited only in one or a few simulation steps. As such, eliminating these states from the behaviour characterisation can significantly improve the efficiency of the algorithm, practically without compromising the accuracy of the characterisation. The function *filter* removes the states where the robots spent less than $T\%$ of the time:

$$m' = \left\{ (h, c) \in m : c > \sum_{i \in m} m[i] \cdot T \right\} . \quad (6)$$

The constant T should be empirically determined. In our experiments, a value of only 1% was enough to drastically reduce the number of states in each characterisation. For instance, the preliminary results showed that on average 99% of the simulation time was spent in only 10% of the visited states.

Distance Between Characterisations

To calculate the distance between two characterisations we chose to use the Bray-Curtis dissimilarity, a well-known measurement for quantifying the difference between samples of abundance data. Bray-Curtis is a modified Manhattan measure, where the summed differences between the variables are standardised by the summed variables of the samples. This measure is within the range of 0 to 1. A value of 0 means that the two samples have are equal, while a value of 1 means the two samples do not share any element.

Adapting the Bray-Curtis dissimilarity behaviour characterisations, the difference b between two characterisations

m_1 and m_2 is given by:

$$b(m_1, m_2) = \frac{\sum_{i \in m_1 \cap m_2} |m_1[i] - m_2[i]| + \sum_{i \in m_1 \setminus m_2} m_1[i] + \sum_{i \in m_2 \setminus m_1} m_2[i]}{\sum_{i \in m_1} m_1[i] + \sum_{i \in m_2} m_2[i]} . \quad (7)$$

3.2 Sampled Average State

The second similarity measure relies on the principles of the Hamming distance measure (see Section 2.2), which was one of the most successful generic similarity measures in previous works with single robot systems [6, 18]. However, this measure relies on the full description of the sensor-effector states of the robot through time. As such, it can not be directly used for swarms of robots because (i) it would not scale with the number of robots, and (ii) the behaviour of an individual robot in a swarm often has a significant stochastic component. To overcome these issues, we propose the following modifications:

- The state of the swarm at a given instant is the average of the sensor-effector states of all robots. This allows scalability in respect to the size of the swarm.
- The state of the swarm is averaged over time windows. This reduces the sensitivity to the initial conditions, and to the stochastic nature of the individual robots behaviour.

The characterisation of an individual is given by:

$$\vartheta = [\{\bar{v}_1(w), \dots, \bar{v}_n(w)\}, w \in \{1..W\}] , \quad (8)$$

where W is the number of time windows and $\bar{v}_i(w)$ is the average value of the i -th sensor/effector over the w -th time window:

$$\bar{v}_i(w) = \frac{W}{T} \sum_{t=(w-1)T/W}^{wT/W} \frac{1}{R} \sum_{r=1}^R v'_{i,r}(t) , \quad (9)$$

T is the total simulation time, R the number of robots, and $v'_{i,r}(t)$ is the normalised value of the i -th sensor/effector of the robot r , at instant t :

$$v'_{i,r}(t) = \frac{v_{i,r} - v_{i,\min}}{v_{i,\max} - v_{i,\min}} , \quad (10)$$

$v_{i,\max}$ and $v_{i,\min}$ are the maximum and minimum values of the i -th sensor/effector, respectively.

The distance between two characterisations ϑ_1 and ϑ_2 is then given by the Manhattan distance between the vectors:

$$d_{Man}(\vartheta_1, \vartheta_2) = \sum | \vartheta_1[i] - \vartheta_2[i] | . \quad (11)$$

4. EXPERIMENTAL SETUP

The proposed generic similarity measures are evaluated over two swarm robotics tasks: aggregation and resource sharing. The generic measures are compared with task-specific measures, and with fitness-based evolution.

Our experimental framework is based on Simbad 3d Robot Simulator [11]. In both tasks, the environment is a 3 m by 3 m square arena bounded by walls. The swarms are homogeneous. Each robot is modelled after the e-puck, but with modifications to the sensor setup. Each robot is circular

¹<http://www.burtleburtle.net/bob/hash/doobs.html>

with a diameter of 8 cm, and is equipped with a differential drive capable of delivering speeds of up to 12 cm/s. The local on-board controllers are recurrent neural networks. The inputs of the neural networks are the normalised values of the sensors of the robot, and there are three outputs: one to control each of the two motors, and one dedicated to completely halt the movement of the robot. Each simulation lasts for 2500 simulation steps, which corresponds to 250 s of simulated time.

4.1 Aggregation Task

Aggregation is a commonly studied task in swarm robotics [21, 2]. In this task, a dispersed robot swarm must form a single cluster in any point of the arena. The swarm has a fixed size of 7 robots. Each robot is equipped with (i) 8 sensors evenly distributed around its chassis for the detection of obstacles (walls or other robots) within a range of 10 cm; (ii) 8 sensors dedicated to the detection of other robots within a range of 25 cm; and (iii) a sensor that returns the percentage of nearby robots (within a radius of 25 cm), relative to the swarm size.

The fitness function F_a is defined as the average distance of the robots to the centre of mass of the swarm, measured at the last instant of the simulation:

$$F_a = 1 - \sum_{i=1}^N \frac{\text{dist}(\mathbf{R}_T, \mathbf{r}_{i,T})}{N}, \quad (12)$$

where T is the simulation length, \mathbf{R}_T is the centre of mass in the last step of simulation, $\mathbf{r}_{i,T}$ is the position of robot i , and N is the swarm size; dist is normalised to $[0, 1]$.

The task-specific behaviour characterisation, used as benchmark, is based on the average distance to the centre of mass of the swarm, and the number of clusters, sampled during the simulation [7]. Considering a simulation with τ temporal samples (50 samples were used in our experiments), the characterisation \mathbf{b}_a is given by:

$$\begin{aligned} \mathbf{b}_a &= \{\mathbf{cm}, \mathbf{cl}\} \\ \mathbf{cm} &= \frac{1}{N} \left[\sum_{i=1}^N \text{dist}(\mathbf{R}_1, \mathbf{r}_{i,1}), \dots, \sum_{i=1}^N \text{dist}(\mathbf{R}_\tau, \mathbf{r}_{i,\tau}) \right] \\ \mathbf{cl} &= \frac{1}{N} [\text{clusterCount}(1), \dots, \text{clusterCount}(\tau)] \end{aligned} \quad (13)$$

The function *clusterCount* returns the number of robot clusters. Two robots belong to the same cluster if the distance between them is less than the robot sensor range (25 cm).

4.2 Resource Sharing Task

In this task, the swarm must coordinate in order to allow each member periodical access to a single battery charging station. The robots should first find the charging station, and then effectively share the station to ensure the survival of all the robots in the swarm. The charging station can only hold one robot at the time.

We use a group of 3 robots for our experiments. Each robot has (i) 8 sensors for the detection of obstacles up to a range of 10 cm; (ii) 8 sensors dedicated to the detection of other robots up to a range of 25 cm; (iii) 8 sensors for the detection of the charging station up to a range of 1 m; (iv) a binary sensor that indicates if the robot is in the charging station or not; and (v) a proprioceptive sensor that reads the current energy level of the robot.

Each robot starts with full energy (1000 units), and spends energy at a rate linearly dependent on motor usage: a robot spends 5 units per second when motors are off, and 10 units of energy per second when motors propel the robot at its maximum speed. The charging station is placed in the centre of the arena, and charges a robot at a rate of 100 units of energy per second. The robots have to be completely stopped in order to charge.

The fitness function F_s used to evaluate the controllers is a linear combination of the number of robots alive at the end of the simulation and the average energy of the robots throughout the entire simulation:

$$F_s = 0.9 \cdot \frac{a_T}{N} + 0.1 \cdot \sum_{t=1}^T \sum_{i=1}^N \frac{e_{i,t}}{T N e_{max}}, \quad (14)$$

where T is the length of the simulation, a_T is the number of robots still alive at the end, N is the number of robots in the swarm, $e_{i,t}$ is the energy of the robot i at time t , and e_{max} is the maximum energy of a robot. The second term of F_s concerning the average energy is included to differentiate solutions where the same number of robots survive.

The task-specific behaviour characterisation is an extension of the characterisation used in previous experiments with this task [8]. The characterisation is a vector of length four, composed by the following behavioural features that are related to the task: (i) The number of robots that reached the end of the simulation alive; (ii) the average energy of the alive robots throughout the simulation; (iii) the average movement of all alive robots; and (iv) the average distance of all alive robots to the charging station. Each of these elements is normalised to $[0, 1]$.

4.3 Configuration of the Algorithms

NEAT [20] is used as the underlying neuroevolution algorithm. The NEAT parameters were the same in all experiments: recurrent links are allowed, crossover rate – 25%, mutation rate – 10%, population size – 200. The remaining parameters were assigned their default value in the NEAT4J² implementation used in our experiments.

The implementation of novelty search follows the description in [15]. We used a k value of 15 nearest neighbours, and individuals are added to the novelty archive with a probability of 2% [13]. The size of the archive is bounded to 500 individuals. When the archive is full, individuals are randomly removed as needed. Novelty search is combined with fitness-based evolution through a linear scalarization (see Section 2.1.1). In all novelty search experiments, the value of ρ was set to 0.7, which means that the score of each individual is based on 70% of the novelty score and 30% of the fitness score. This value was empirically chosen, and in agreement with previous experiments [8].

For the *combined state count* measure, the filter threshold T was set to 1% in all experiments, and the discretisation level K was set to 3. For the *sampled average state* measure, three values of W were tested: 1, 10, and 50, which correspond to time windows of 250 s, 25 s, and 5 s, respectively. In both generic similarity measures, the values coming from the sensor arrays (composed of 8 sensors for the detection of obstacles, other robots, or the charging station) were compressed in four values. These four values represent the closest distance measured at the front of the robot, left,

²Version 1.0. <http://neat4j.sourceforge.net>

right, and back. This compression was done to reduce the number of states (in the *combined state count* measure), and to reduce the length of the characterisation (in the *sampled average state* measure).

Each controller was evaluated in 10 simulations, randomly varying the initial positions and orientations of the robots. The fitness scores obtained in each simulation are combined to a single value using the harmonic mean as advocated in [1]. The behaviour characterisations obtained in the multiple simulations are also merged in a single characterisation through an element-wise average (in the task-specific measures and in *sampled average state*), and by summing the state counts (in *combined state count*). The best individuals of each generation were post-evaluated with 50 simulations, in order to obtain a more accurate estimate of their fitness.

5. RESULTS

The following treatments were applied to each task. Each evolutionary method was evaluated in 10 independent evolutionary runs. The parameters of each method were set as specified in Section 4.3.

- SC Combined state count
- AS-1 Sampled average state with $W = 1$
- AS-10 Sampled average state with $W = 10$
- AS-50 Sampled average state with $W = 50$
- TS Novelty with task-specific similarity measure
- Fit Fitness-based evolution

The quality of the solutions evolved with each evolutionary method is depicted in Figure 1. The boxplots represent the highest fitness score found until a given generation, in each evolutionary run of each treatment. The depicted results are further explained below.

5.1 Aggregation

As the results show (Figure 1 – Aggregation), the fitness function is not deceptive, as fitness-based evolution can almost always reach high quality solutions. The most notorious advantage of novelty search is its capacity of avoiding deception. However, previous work [7] has shown that even in non-deceptive swarm robotics tasks, novelty search can offer a number of advantages. As such, it is still valuable to analyse the performance of novelty search with generic behaviour similarity measures in this non-deceptive task.

In early stages of evolution (at generation 20), novelty search has an advantage over fitness-based evolution, confirming that novelty search quickly bootstraps the evolutionary process [7, 17]. All similarity measures, except for *combined state count* were superior to fitness-based evolution (p -value < 0.05 , Mann-Whitney U test).

Around the middle of evolution (generation 75), the differences between the treatments are less pronounced. By the end of the evolution, the task-specific similarity measure is only superior to the state count measure (p -value < 0.05). This absence of significant difference between treatments is actually a promising result. Previous work [7] has shown that when the behaviour similarity measure is poorly chosen, the performance of novelty search tends to degrade significantly, regarding the quality of the solutions evolved. In our experiment, the generic measures yielded results similar to fitness-based evolution and to the task-specific measure, which suggests that the generic measures are acting as effective behaviour similarity measures.

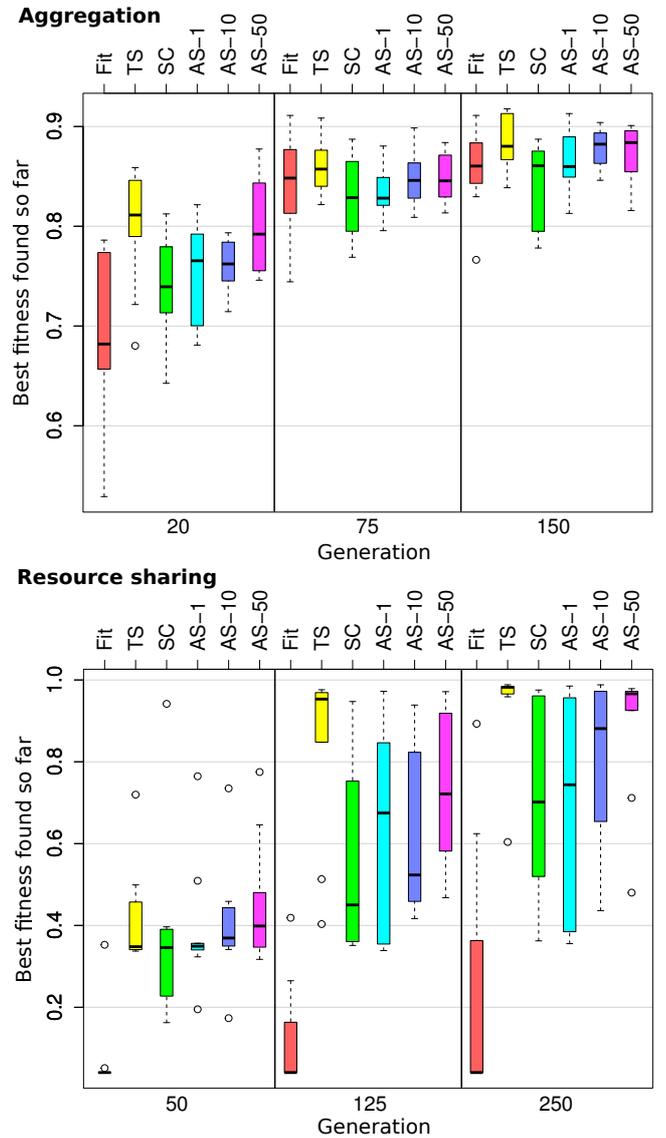


Figure 1: Performance comparison of the evolutionary treatments in both tasks, regarding the highest fitness score achieved at different stages of the evolutionary process. The boxplots represent the distribution of the fitness scores obtained in the 10 evolutionary runs of each treatment.

5.2 Resource Sharing

As previous experiments have shown [8], the resource sharing task is inherently deceptive. In particular, fitness-based evolution tends to get stuck in two local maxima: (i) The robots do not move at all in order to conserve energy and survive longer, and as a consequence, they can not find the charging station and all the robots run out of energy (fitness score around 0.04); and (ii) when a robot finds the charging station, it occupies it and never leaves, condemning the other robots (fitness score around 0.38). The deceptiveness of this task makes it especially suitable to solve using novelty search. As such, this task is a good benchmark to evaluate if the behaviour similarity measures are capable of avoiding deception and guiding evolution towards good solutions.

At the early stages of evolution (generation 50, see Figure 1 – Resource sharing), almost all runs of fitness-based evolution are still stuck in the local maximum where the robots do not move. On the other hand, all treatments based on behavioural novelty could successfully bootstrap the evolution. At this early stage, there are still no significant differences between the novelty based treatments. By the middle of the evolutionary process, the task-specific similarity measure stands out, being superior to all the treatments (p -value < 0.05 , Mann-Whitney U test), except for **AS-50**. There are no statistically significant differences between generic similarity measures at this stage.

Comparing the final results obtained with the different treatments, the task-specific measure clearly outperformed the other measures and fitness-based evolution, see Figure 1 – Resource sharing, generation 250. However, all novelty based treatments were superior to fitness-based evolution (p -value < 0.05), and more or less consistently, all reached high fitness scores. Regarding the generic similarity measures, the **AS-50** treatment stands out, being significantly superior to **SC** and **AS-1** (p -value < 0.05).

5.3 Combined State Count

In both tasks, the *combined state count* measure was the least effective measure. Nevertheless, the performance was close to the *sampled average state*, which contrasts with the results in [6]. To understand the inferior performance of *combined state count*, we analysed the sensor-effector states that are visited with each individual (Figure 2).

The increasing average number of states depicts the increasing complexity of the solutions throughout evolution. However, the average number of common states does not follow this trend. Since the distance between two state count characterisations is determined by the states they share, this distance can lose accuracy if the characterisations share few states. In the extreme case, if no states are shared, the distance value is always the same. To overcome this issue, we suggest that the similarity between states should also be considered in the distance metric, besides the count of each state. This way, the distance will maintain its accuracy, regardless of the number of shared states. Further studies are required to assess the viability of this approach.

5.4 Sampled Average State

Regarding the *sampled average state* technique, the most important factor to study is the influence of the parameter W . This parameter controls the length of the characterisation and how accurately it captures the temporal component of the robots behaviour. In the aggregation task, there was no significant difference among the treatments with different W values (p -value < 0.05). On the other hand, in the resource sharing task there is a trend in the results: the higher the W , the better the performance of the evolutionary process, regarding the quality of the solutions. The treatment with $W = 50$ delivers significantly higher fitness scores than the treatment with $W = 1$ (p -value < 0.05).

The reason for the different impact of the W value in different tasks is still not clear. Our hypothesis is that the difference is due to the degree of behaviour regularity necessary to solve each task. The aggregation task can be solved using a regular pattern of behaviour, almost a reactive approach. As such, a low W value might be sufficient to adequately characterise the behaviour of the swarm. On the

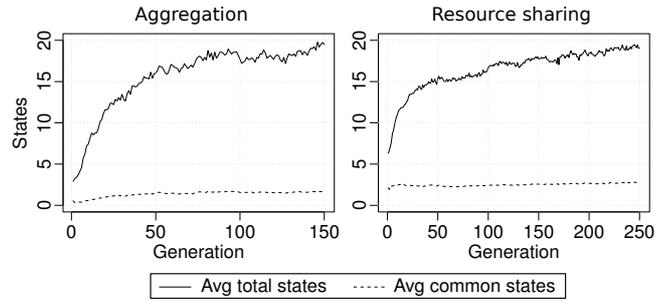


Figure 2: Average number of sensor-effector states visited by each population individual (after the filtering step), compared with the average number of states that each individual shares with the current population and the novelty archive.

other hand, the resource sharing task requires a more sequential behaviour, which involves first finding the charging station, and then a different behaviour for sharing it with the other robots. As a consequence, higher W values might be preferred, as they allow the sequential component of the behaviour to be adequately captured. Further experiments are required to confirm or reject this hypothesis.

6. CONCLUSION

We proposed two generic similarity measures for the domain of evolutionary swarm robotics, and used them to drive novelty search. The proposed measures rely on the principle that by analysing the microscopic behaviour of the robots of the swarm, it is possible to obtain a characterisation of the swarm behaviour as whole. The microscopic behaviour of each robot is exclusively based on the sensor and effector values of the robots, keeping the characterisation completely independent of the experimenter’s understanding of the task.

The proposed measures were tested in two distinct tasks, and compared with carefully crafted task-specific measures. The results showed that the performance obtained with the generic measures is close to the performance obtained with the task-specific measures, regarding the quality of the evolved solutions. In each task, the highest scoring generic measures were not significantly worse than the task-specific measure. Furthermore, the results show that the advantages of novelty search identified in previous work [7, 9] hold with the generic measures: novelty search excelled in the earlier stages of evolution and was successful in circumventing deception. Our results suggest that the proposed measures are sufficiently generic to scale to complex robotics tasks. In the resource sharing task, for instance, the robots had a reasonably large number of sensors and effectors, originating a large search space. Nevertheless, the generic novelty measures could deliver a reasonably good performance.

In the comparison between the proposed generic similarity measures, we found that the *sampled average state* achieved the best results in both tasks. However, from a general perspective, this measure is associated with a number of limitations: (i) characterisations can become too long if there is a high number of sensors/effectors and a high value of W is necessary; (ii) it is not applicable to tasks where simulations can have different lengths; and (iii) in tasks where the robots of the swarm are performing different sub-tasks simultane-

ously, averaging the sensor-effector states of all robots can result in a meaningless characterisation. On the other hand, the *combined state count* measure does not suffer from these limitations, despite the inferior performance verified in the two tasks presented in this paper. As such, we contend that the state count approach should not be dismissed, and it should be further improved in future work. More experiments, with different tasks, are also needed in order to determine how well our results generalise, and clarify which measures are more suitable for different types of tasks.

The use of novelty search with generic behaviour similarity measures, in combination with traditional fitness-based evolution, opens interesting possibilities in the domain of evolutionary swarm robotics. First, it facilitates the use of straightforward fitness functions. There is no need to shape the fitness function in order to avoid local maxima, since novelty search circumvents that issue, without relying on additional information provided by the experimenter. The use of generic measures is a step towards evolving complex solutions with minimal intervention from the experimenter. Second, generic measures can potentially be used to unveil a true diversity of solutions, with the evolved diversity not being conditioned by the experimenter.

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7. REFERENCES

- [1] E. Bahgeçi and E. Şahin. Evolving aggregation behaviors for swarm robotic systems: A systematic case study. In *Swarm Intelligence Symposium*, pages 333–340. IEEE Press, 2005.
- [2] G. Baldassarre, S. Nolfi, and D. Parisi. Evolving Mobile Robots Able to Display Collective Behaviors. *Artificial Life*, 9(3):255–268, 2003.
- [3] G. Baldassarre, V. Trianni, M. Bonani, F. Mondada, M. Dorigo, and S. Nolfi. Self-Organized Coordinated Motion in Groups of Physically Connected Robots. *IEEE Transactions on Systems, Man, and Cybernetics*, 37(1):224–239, 2007.
- [4] E. Şahin. Swarm robotics: from sources of inspiration to domains of application. In *2004 International Conf. on Swarm Robotics*, volume 3342 of *LNCS*, pages 10–20. Springer-Verlag, 2005.
- [5] G. Cuccu and F. J. Gomez. When Novelty Is Not Enough. In *European Conf. on the Applications of Evolutionary Computation*, volume 6624 of *LNCS*, pages 234–243. Springer-Verlag, 2011.
- [6] S. Doncieux and J.-B. Mouret. Behavioral diversity measures for Evolutionary Robotics. In *IEEE Congress on Evolutionary Computation*, pages 1–8. IEEE Press, 2010.
- [7] J. Gomes, P. Urbano, and A. L. Christensen. Introducing novelty search in evolutionary swarm robotics. In *International Conf. on Swarm Intelligence*, volume 7461 of *LNCS*, pages 85–96. Springer-Verlag, 2012.
- [8] J. Gomes, P. Urbano, and A. L. Christensen. Progressive Minimal Criteria Novelty Search. In *Ibero-American Conf. on Artificial Int.*, volume 7637 of *LNAI*, pages 281–290. Springer-Verlag, 2012.
- [9] J. Gomes, P. Urbano, and A. L. Christensen. Evolution of swarm robotics systems with novelty search. *Swarm Intelligence*, 2013. In press.
- [10] F. J. Gomez. Sustaining diversity using behavioral information distance. In *Genetic and Evolutionary Computation Conf.*, pages 113–120. ACM Press, 2009.
- [11] L. Hugues and N. Bredeche. Simbad: An Autonomous Robot Simulation Package for Education and Research. In *From Animals to Animats 9*, volume 4095 of *LNCS*, pages 831–842. Springer-Verlag, 2006.
- [12] P. Krcah. Solving deceptive tasks in robot body-brain co-evolution by searching for behavioral novelty. In *International Conf. on Intelligent Systems Design and Applications*, pages 284–289. IEEE Press, 2010.
- [13] J. Lehman and K. O. Stanley. Efficiently evolving programs through the search for novelty. In *Genetic and Evolutionary Computation Conf.*, pages 837–844. ACM Press, 2010.
- [14] J. Lehman and K. O. Stanley. Revising the evolutionary computation abstraction: minimal criteria novelty search. In *Genetic and Evolutionary Computation Conf.*, pages 103–110. ACM Press, 2010.
- [15] J. Lehman and K. O. Stanley. Abandoning Objectives: Evolution Through the Search for Novelty Alone. *Evolutionary Computation*, 19(2):189–223, 2011.
- [16] J.-B. Mouret. Novelty-Based Multiobjectivization. In *New Horizons in Evolutionary Robotics*, volume 341 of *Studies in Computational Intelligence*, pages 139–154. Springer-Verlag, 2011.
- [17] J.-B. Mouret and S. Doncieux. Overcoming the bootstrap problem in evolutionary robotics using behavioral diversity. In *IEEE Congress on Evolutionary Computation*, pages 1161–1168. IEEE Press, 2009.
- [18] J.-B. Mouret and S. Doncieux. Encouraging Behavioral Diversity in Evolutionary Robotics: An Empirical Study. *Evolutionary Computation*, 20(1):91–133, 2012.
- [19] A. L. Nelson, G. J. Barlow, and L. Doitsidis. Fitness functions in evolutionary robotics: A survey and analysis. *Robotics and Autonomous Systems*, 57(4):345–370, 2009.
- [20] K. O. Stanley and R. Miikkulainen. Evolving Neural Network through Augmenting Topologies. *Evolutionary Computation*, 10(2):99–127, 2002.
- [21] V. Trianni, R. Groß, T. H. Labelle, E. Şahin, and M. Dorigo. Evolving Aggregation Behaviors in a Swarm of Robots. In *European Conf. on Artificial Intelligence*, volume 2801 of *LNCS*, pages 865–874. Springer-Verlag, 2003.
- [22] V. Trianni, S. Nolfi, and M. Dorigo. Cooperative hole avoidance in a swarm-bot. *Robotics and Autonomous Systems*, 54(2):97–103, 2006.
- [23] L. D. Whitley. Fundamental Principles of Deception in Genetic Search. In *Foundations of Genetic Algorithms*, pages 221–241. Morgan Kaufmann, 1991.
- [24] N. Zaera, D. Cliff, and J. Bruton. (Not) Evolving Collective Behaviours in Synthetic Fish. In *International Conf. on the Simulation of Adaptive Behavior*, pages 635–644. MIT Press, 1996.