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Detecting evolutionary bias in the decision-making of robotic swarms

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Abstract. This paper presents a simple and easy to use, yet powerful method for identifying evolutionary bias in neuro-controllers, based on classical Shannon entropy in one specific domain of swarm robotics. We demonstrate its application for assessing the quality of one neural network-based decision-making controller for swarm opinion formation, evolved for the site selection task. The preliminary results, based on simulated swarm behaviour recorded in three experimental conditions and nine trials overall, reveal the benefits and the consistency of the applied measure and its ability to discern various opinion formation trends. Such a tool could help automate the process of bench-marking controllers and assess their quality with respect to evolutionary bias, and thus minimize designers effort, while at the same time provide better models performing consistently across conditions.

Keywords: Evolutionary robotics · Swarm robotics · Collective decision-making.

1 Introduction

Evolutionary bias is a well-known artifact of neuro-controllers developed with evolutionary techniques [6, 1, 2]. It affects different controllers to a different extent and can have unpredictable divers effects on swarm behaviour, however, it is not easy to identify its impact based only on the fitness function, as often the best genotypes can have a strong bias, whereas genotypes with lower fitness may have milder bias and behave more consistently across conditions. Therefore, it takes a significant amount of manual inspection and profiling in order to handpick the optimal neural network model (NNM), which requires a costly time-consuming designer effort. In order to automate and simplify this process, we need rigorous measures and tools that apply to various scenarios in this domain.

In this paper, we demonstrate a method, based on Shannon entropy [5], for characterising the dynamics of opinion formation in a robotic swarm engaged in a site selection task [3]. To estimate the magnitude of the probability of future opinion divergences within the swarm, we compute the entropy of a subset of the swarm (represented by the robots' IDs) based on local proximity information and robots' opinions. We highlight the benefits of the method for better understanding the behaviour of NNMs and detecting evolutionary bias automatically at low computational cost. The proposed method could contribute to an improved design process, reducing the amount of manual inspection required for NNM evaluation, while providing better and more consistent models for post-evaluation.

2 Method

Due to the lack of space, we will only briefly describe the site selection scenario used in our study. For further details we refer the reader to [3]. The environment consists of an arena of $2m \times 2m$ in which three sites of varying quality, proportional to the size of the corresponding site (i.e., the white area, see Fig. 1a) that covers 80%, 50% or 20% respectively of the arena and are denoted with L for large, M for medium, and S for small. In the studied experimental conditions each site appears in a different position, i.e., Cond_1 (L, M, S), Cond_2 (S, L, M), and Cond_3 (M, S, L) (see Fig. 1b). In [3], a swarm of 21 simulated e-puck2 robots [4] explore the environment and disseminate their opinions with the aim to reach a consensus on the correct option representing the position of the best quality site (left, middle, or right) for at least 10 seconds. Random explorations are followed by opinion dissemination, during which each robot shares its current belief only with its closest disseminating neighbour (in 50cm range). The individual decision-making mechanism for opinion formation of every robot is controlled by a dynamic neural network, synthesized with evolutionary computation techniques on all three conditions simultaneously and is cloned on each of the 21 robots forming a homogeneous swarm. All conditions were tested in 50 trials lasting 2400s each. At the beginning of each trial the robots are initialised

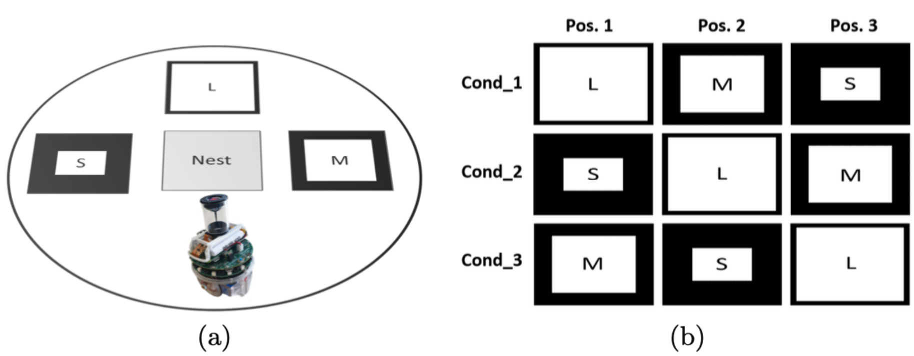


Fig. 1. a) The site-selection scenario with nest and three sites – L, M, and S. b) The position of each site in the three experimental conditions.

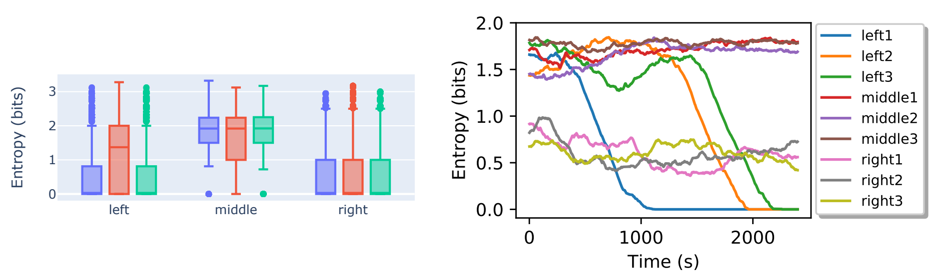
with different random seeds, which influence their initial position and orientation and the noise added to their sensors and motors.

The standard measure for characterising swarm convergence to consensus is the number of robots holding the correct opinion. This approach, however, disregards the relative position of the robots in the arena with respect to each other. To capture such local proximity information, which impacts the exchange of opinions within the swarm, we define a subset of the swarm (consisting of robot IDs), including all pairs of closest neighbours that disseminate different opinions in one particular moment. We propose that the entropy of this subset could provide a relevant indicator of the potential magnitude of future opinion divergences within the swarm.

3 Results

The robustness of the NNMs was investigated in a configuration with 80%, 70%, and 60% ratios, which is more challenging than the original one, and the results revealed strong evolutionary bias for certain neuro-controllers.

To examine this artifact of swarm behaviour, we have analysed the data recorded in nine trials using the same neuro-controller for the three experimental conditions initialised with three different random seeds each. To characterise the dynamics of opinion formation within the swarm, at every iteration step of each trial we computed the entropy using the above method. The results reveal consistent convergence to consensus in Cond_1 for all three seeds, unstable consensus for Cond_3 and sporadic consensus for Cond_2. The entropy distributions for the duration of all nine trials (see Fig. 2a) indicate that in Cond_1 (left is best) and Cond_3 (right is best) the swarm reached consensus (i.e., zero



(a) (b)

Fig. 2. (a) Distribution of entropy levels computed at each iteration of the studied nine trials (total of 24,000 samples each). Left, middle and right reflect the position of the best site in a particular trial. Blue, red and green correspond to the three different random seeds used to initialize the swarm in different trials. (b) The entropy time series are smoothed with a moving average filter (window size=6,000 over 24,000 samples in total per trial). 1, 2 and 3 correspond to the three different random seeds.

entropy) more frequently and/or for longer periods than in Cond_2 (middle is best). To elucidate the swarm opinion formation dynamics as the trials unfold, we applied a moving average filter on the entropy time series with a window size of 6,000 over the total of 24,0000 data points. The results (see Fig. 2b) shed more light on the nature of evolutionary bias for this particular NNM, which allows the swarm to converge to a stable consensus for Cond_1, although with considerable variations in consensus time, while in Cond_2 and Cond_3 the convergence is intermittent and sporadic. Note that the minimal consensus period of 10s corresponds to 100 samples, which are largely inhibited by the applied window. In Cond_2 the oscillations in robots' opinions result in higher entropy levels, suggesting that consensus is rather accidental than deliberate. These results reveal a significant evolutionary bias in swarm behaviour between the three experimental conditions, which exhibit very different entropy profiles, whereas within each condition the trends in entropy levels are rather similar.

4 Conclusion

This preliminary investigation sheds light on specific trends induced by evolutionary bias in one particular decision-making mechanism evolved for the site selection task. The applied Shannon entropy measure elucidates different types of bias associated with three experimental conditions and provides a consistent characterisation across trials. The results indicate the potential of this benchmark method for supporting and automating the evaluation of evolved controllers, independent from their fitness function, which provides no information related to evolutionary bias. Rigorous tools and measures could alleviate designers in their quest for the best controllers and facilitate the development of more consistent models by mitigating evolutionary bias. The analytic detection of cyclic oscillations in opinion shifts could allow the automatic rejection of a malfunctioning controller at low cost. Future research will validate the approach with a range of decision-making controllers and expand its realm to further scenarios in this domain, such as collective perception.

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