The Cost of Communication: Environmental Pressure and Survivability in mEDEA

Andreas Steyven
School of Computing
Edinburgh Napier University
Edinburgh, Scotland, UK
a.steyven@napier.ac.uk

Emma Hart
School of Computing
Edinburgh Napier University
Edinburgh, Scotland, UK
e.hart@napier.ac.uk

Ben Paechter
School of Computing
Edinburgh Napier University
Edinburgh, Scotland, UK
b.paechter@napier.ac.uk

ABSTRACT

We augment the mEDEA algorithm to explicitly account for the costs of communication between robots. Experimental results show that adding a costs for communication exerts environmental pressure to implicitly select for genomes that maintain high energy levels. We compare our two methods which vary broadcasting based on the individuals fitness to vanilla mEDEA bundled with an explicit selection method under these new conditions and find that biasing broadcasting has a negative effect on survivability.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic methods*

Keywords

Evolutionary Robotics; Environment-driven; Online Evolution

1. INTRODUCTION

In previous research [4] we implemented an explicit fitness measure into mEDEA [1] that influences the spread of genomes through the population in order to increase survivability, thus, ensure the integrity of the swarm. We dubbed the algorithm mEDEA$_{rf}$ — mEDEA with relative fitness.

In mEDEA a robot's controller is encoded in its genome which is constantly broadcast in a close range. A random selection from a list of the received genomes during the generation determines the controller for the next generation. In mEDEA$_{rf}$ the broadcasting is varied either by reducing the range or probability of broadcasting depending on the explicit fitness value to favour the spread of genomes that produce controller which maintain a higher energy balance. We compared mEDEA$_{rf}$ to mEDEA where the random selection is replace with an explicit selection method.

Our results suggested that although using the relative fitness value in either way improved survivability, adjusting the broadcasting mechanism should conserve energy. In this paper we derive an energy model to account for the cost for communication and implemented it into both algorithms to test this hypothesis. We give a briefly overview of the experiments conducted and the results obtained.

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2. METHOD

Two different methods were introduced in mEDEA$_{rf}$ that change the broadcasting mechanism in mEDEA by varying a) the probability to broadcast and b) adjusting the broadcast radius, in proportion to the fitness value. Both mechanisms bias the broadcast towards fitter individuals. For an in-depth description of the mEDEA algorithm and the details of our proposed modifications the reader is referred to [1] and [4] respectively.

To calculate the cost of communication for the simulated ePuck robots in Roborobo [2], we derive an energy model based on the Free-Space Model [5] (equation 1) which is used in wireless sensor network simulations. This field of research makes extensive use of the low power communication modules used in experiments[1] using the ePuck robot platform [6].

$$E_{\text{tx}}(n,d) = n \times E_{\text{elec}} + n \times \epsilon_{\text{amp}} \times d^2 \tag{1}$$

E_{elec} is the basic charge to run the module, ϵ_{amp} the costs for signal amplification which is multiplied by the *d*istance squared and n represents the number of *bits* in a transmission. n is constant as genome broadcasts only vary in content, not length. Values for $E_{\text{tx}}(r_{\max}) = 0.075$ and $E_{\text{tx}}(r_{\min}) = 0.028$ have been chosen following limited empirical testing. The energy required for receiving is constant and 7% higher than the $E_{\text{tx}}(r_{\max})$, due to the low-power nature of the signals which requires signal reconstruction circuits [7].

In order to evaluate the dependence on energy we amend the experimental setup as follows: maximum energy per robot adjusted from 2000 to 15000, initial energy of a robot lowered to 750 (enough to survive half a generation) and energy pucks limited to 75. Further, the algorithm was adapted to prevent robots from broadcasting in empty neighbourhoods to prevent fruitless genome distribution attempts.

3. EXPERIMENTS

Experiments were designed to evaluate the following hypothesis: When accounting for the cost of communication, biasing the spread of gnomes in mEDEA$_{rf}$ outperforms continuous broadcast combined with an explicit selection in

[1]TI CC2420 in [3] and Bluetooth module LMX9820a in [6]

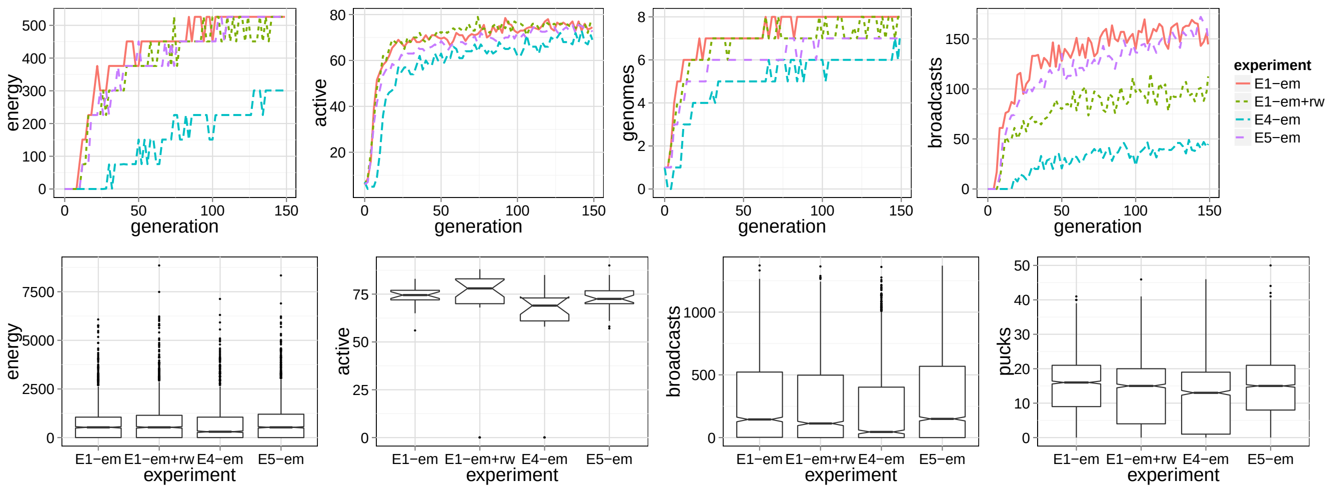

Figure 1: Figures show the energy, number of active robots and genomes received for each of the experiments $\mathbf{E1}_{em}$, $\mathbf{E1}_{em}$+rw, $\mathbf{E4}_{em}$ and $\mathbf{E5}_{em}$. Box plots showing values at generation 150.

terms of active robots and the maintained energy level at the end of the last generation.

Four different experiments were conducted based on the experiments in [4]: **E1**$_{em}$: baseline experiment, vanilla mEDEA using the energy model with random individual selection; **E1**$_{em}$**+rw**: as E1$_{em}$, but using roulette-wheel selection as individual selection method; **E4**$_{em}$: using a fitness proportionate probability to broadcast; **E5**$_{em}$: varying the broadcast radius proportionate to the fitness.

4. RESULTS AND ANALYSIS

Figure 1 shows the median[2] result over 30 repeated runs at the end of the generation.

In E1$_{em}$ energy can be maintained by reducing broadcasting or gathering energy pucks. In cases where the broadcasting rate is fixed, avoiding others is the only option, which, however, is not conducive to spreading the genome.

The results[3] show that:

E1$_{em}$ broadcasts most and gathers the most pucks. At the other extreme E4$_{em}$ (frequency variation) broadcasts least and also gathers fewest pucks: it experiences the least pressure to collect as it can maintain energy by reducing broadcasting. However, the reduced environmental pressure leads to a much slower increase in energy and fewer active robots compared to the unbiased broadcast experiments.

In E5$_{em}$, although there is the same amount of broadcasting as in E1$_{em}$, it does not lead to a significant difference in active robots c.f. E4$_{em}$. The evolved behaviour leads to significantly fewer pucks being collected.

The mechanisms in E4$_{em}$ and E5$_{em}$ lower the environmental pressure by preventing less fit individuals from communicating. High fitness individuals will broadcast with high probability or full range hence bear high costs; in contrast low fitness robots rarely broadcast thus save energy. The two methods differ in that in E5$_{em}$ even with $r = 0$ according to eq. 1 there is still a basic cost.

[2]as a Shapiro-Wilk test showed that the results were not normally distributed

[3]A Wilcoxon Rank-Sum test with a significance level $\alpha = 0.05$ was used to determine statistical significance.

5. CONCLUSION

We introduced an energy model based on the Free-Space model to account for the cost of communication in mEDEA$_{rf}$. Experimental results showed this exerts environmental pressure to implicitly select for genomes that maintain high energy levels. Comparing the method of varying the broadcasting based on fitness to mEDEA alone and with roulette-wheel genome selection shows that although marginal, the latter approaches outperform the mEDEA$_{rf}$ methods, as they partially reverse the effect of the environmental pressure.

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