GACS, an evolutionary approach to the spatial coordination of agents

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Abstract

Our approach to the spatial coordination of agents is based on parametrized force fields. Through a quantitative comparison on a complex spatial coordination problem treated with a similar approach by Balch and Hybinette, we show that our system, GACS, finds a population of solutions as efficient as the one found with their representation though ours generates simpler solutions and has required much less involvement from the designers [1].

1. Introduction

Designing large scale realistic simulations is a more and more common industrial necessity, *e.g.* for movies, video games or military simulations. But it is still a challenging research problem in computer science. In particular, agents in these worlds should at least be correctly positioned and oriented with respect to each other and to their environment, which is the spatial coordination problem.

Our approach to this problem consists in replacing the manual selection of potential solutions by the operation of a multi-criteria genetic algorithm (GA). The reader can find a detailed presentation of our platform, GACS, in [3].

Here, we provide a global comparison between GACS and Balch's approach thanks to a methodological innovation consisting in merging Pareto fronts.

2. Experimental set-up

Our experiments reproduce those of Balch and Hybinette on a formation maintenance problem [1], they follow the same specifications as in [3]. However, the performance criteria differ. We define three separate criteria: (*formation maintenance*, *obstacle avoidance* and *goal reach*).

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• Let $P_i^t, i \in \{1, ..., 4\}$ be the correct position in the formation at instant t. The fitness f_1 for the *formation maintenance* criterion is:

$$f_1(a) = \frac{1}{t_M} \sum_{t=1}^{t_M} r[e_f(a)],\ a \in \mathcal{A} \tag{1}$$

where r is a punishment function from the position error with respect to the ideal formation configuration, $\mathcal{A}$ the group of agents, t_M is the run duration and e_f is a function giving the formation error:

$$e_f(a) = \sum_{k=1}^{4} |\overrightarrow{A_k P_k}|, r(x) = \begin{cases} 1.0 & \text{if } x < 0.05 \\ \frac{0.5-x}{0.45} & \text{if } x \in [0.05, 0.5] \\ 0.0 & \text{if } x > 0.5 \end{cases} \tag{2}$$

• The obstacle avoidance criterion f_2 measures the capacity of agents to avoid obstacles while staying close to them:

$$f_2(a) = \frac{P_o}{P_o + e^q} \tag{3}$$

where P_o is the sum over each steps of one run of the number of agents inside an area defined by obstacles of doubled size, and q is the number of collisions obtained by counting for each step the number of agent colliding with each obstacle.

• The *goal reach* criterion f_3 is given by the average distance of all agents to the goal at the end of a run, as in [3].

In order to make a comparative study between our model and Balch's, we used his schema-based controller described in [1, 3], improved with the possibility to tune the parameters with our GA.

We run our GA with the above criteria on Balch's approach as well as on ours. In both cases, we run 10 separate evolutions on 10 different computers during 335 generations. Each run is launched with a population of $n_P = 100$ individuals, the maximum time assigned to a simulation is

$t_M = 500$ and every evaluation of a controller is realized from $n_E = 25$ initial positions.

Each run generates a Pareto front. Then we merge the 10 Pareto fronts by selecting the population of non dominated individuals over the 10 runs. Finally, we merge the Pareto front obtained with Balch's approach with the one obtained with GACS.

3. Results

With Balch's approach, the final Pareto front after the merge of 10 runs contains 332 individuals (min = 10 individuals from one machine, max = 60). With GACS, it contains 240 individuals (min = 6 individuals from one machine, max = 44). In both cases, all runs contribute significantly to the final Pareto front. They consistently converge towards individuals of comparable performance.

After discarding all individuals which obtain less than 90% on the *goal reach* criterion, the filtered population contains 118 individuals, among which 62 (52.54%) come from Balch's approach and 56 (47.46%) are generated by GACS.

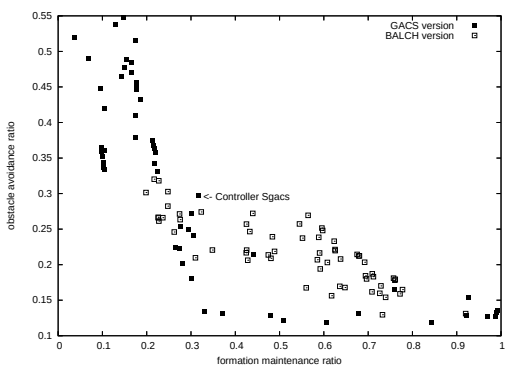

Figure 1. Two-dimension projection of the final Pareto front after having filtered individuals scoring less than 90% on the *goal reach* criterion.

The projection of this final population in a space defined by the *formation maintenance* and *obstacle avoidance* criteria is shown on figure 1.

4. Discussion

The population obtained with GACS and with Balch's approach do not completely dominate each other. Though the relative positions of the non dominated solutions in the criteria space is different each time, the non dominated controllers generated by Balch's approach are more often around the center of the front while GACS controllers are by the sides. This result speaks in favor of Balch's approach since solutions around the center of the Pareto front represent a better compromise between the criteria. But there are always some non dominated solutions generated by GACS in the central area, too.

Our evolved version of Balch's solution requires to tune significantly less parameters than ours, but this results from the careful design of the schemata by an expert who used his intuition to specify all other parameters in advance. Our approach spares this expert involvement. Furthermore we can fix some parameters and run our GA on the other ones. In that sense, our formalism is more general than Balch's with respect to evolutionary optimization.

And finally, our system can find much simpler solutions than the one generated by Balch's approach. The controller S_{gacs} only uses 3 straightforward forces and can be a fruitful source of inspiration for an expert.

5. Conclusion

The automatic exploration and selection properties provided by our platform bring methodological advantages over other bottom-up approaches relying either on manual design or on weaker evolutionary methods: they find simpler solutions and significantly reduce the implication of the designer without being detrimental to the performance. From an industrial point of view, this result justifies the use of GACS rather than Balch's approach.

Though being dedicated to spatial coordination problems, our framework is not specialized towards any particular subclass of such problems, and has already been applied successfully a multi-agent instance of the flock-herding problem [2] or some unpublished industrial military simulations.

References

[1] T. Balch and M. Hybinette. Social Potentials for Scalable Multi-Robots Formations. In *IEEE International Conference on Robotics and Automation (ICRA-2000)*, pages 73–80, 2000.

[2] F. Flacher and O. Sigaud. Spatial Coordination through Social Potential Fields and Genetic Algorithms. In *From Animals to Animats 7: Proceedings of the Seventh International Conference on Simulation of Adaptive Behavior*, pages 389–390, Cambridge, MA, 2002. MIT Press.

[3] F. Flacher and O. Sigaud. BASC, a Bottom-up Approach to automated design of Spatial Coordination. In S. Schaal, A. Ijspeert, A. Billard, S. Vijayakumar, J. Hallam, and J.-A. Meyer, editors, *From Animals to Animats 8: Proceedings of the Seventh International Conference on Simulation of Adaptive Behavior*, pages 435–444, Cambridge, MA, 2004. MIT Press.