Intrinsic Emergence Boosts Adaptive Capacity

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1. INTRODUCTION

The essential part of research about evolutionary algorithms or any optimisation algorithm in general is the discovery of mechanisms to improve the search, when the problem is characterized by a huge search space. Many meta-heuristics and hybridisations of those algorithms are invented and compared with their capacity to traverse this search space in the most effective way. One alternative approach when facing the problem of the space dimension is to discover some clever ways to reduce it. The notion of "intrinsic emergence" originally inspired by the developments of Crutchfield and Mitchell appears to be very helpful [2].

According to them and other authors, and as further discussed in [1], a macro property, labelled as "emergent", should supply some mechanical and non-human observer with additional functional sense. This "functional device" replaces the common need of a human observation to characterize emergence. Indeed, as shown in [1], this concept offers an interesting way to encode macroscopically the genome of a multi-agent system, and by doing so, to reduce temporally the size of the search space. In [1], the different ways to observe the search space were tested randomly, while here, for greater coherence, the search in the "space of observables" extends the idea and uses an evolutionary mechanism. This combination of the two evolutionary searches is the core of the new algorithm presented in this poster.

To test the effectiveness of this approach, the problem treated here is the evolution and the discovery of a cellular automata (CA) able to simulate a binary adder. This problem is chosen for different reasons. First of all, CA is the favorite computational platform to illustrate emergent phenomena. Secondly, due to the simplicity of CA formalisation, the generalisation of the new approach to other multi-agents systems will be easy. A final major reason is the engineering interest in binary addition. Indeed, this task is more relevant than "density classification" or "synchronisation" for computer applications.

The CA used here is bi-dimensional with periodic boundaries and characterized by the classical 8-cells Moore neighbourhood. The state domain is the binary set $\{0,1\}$ and the state update law is synchronous. This update law composed of the CA rules table is coded in a binary array. It is composed by all possible 2^8 update cellular cells which are indexed by the corresponding neighbourhood. We adopt a non-uniform version of CA which offers more computional power than the uniform case. The whole problem consists in achieving this addition task for given couples of binary numbers.

2. A USEFUL WAY TO OBSERVE CA

Even if the variety parameters is limited to three values, the space cardinality is still around 10^{231}, making it hard for a classical genetic algorithm (GA) to find the global optimum in a decent time. Based on the intrinsic emergence concept, an original way to observe the CA is discussed in [1]: the macro observable consists in masking some of the eight neighbours of all cells to be updated. As a result the search space is considerably reduced. Consequently, at any update step of the CA, the algorithm does not take into consideration the masked neighbours in order to compute the new state.

The CA working is not modified by excessive simplification. Indeed, the mask determines a set of neighbourhood states that gives an identical result following the given rules (and its variety). Only the unsmasked cells state is important. This fact allows us to compress the rules coding. Thus, we can strongly reduce the space needed for coding the rules and therefore the whole search space. If the number of masked cells is denoted by l_m, we have $(8 - l_m)$ unmasked cells and the rules are coded on $v2^{8-l_m}$. The size of the search falls down to 2 to the power $v2^{8-lm}$.

Now all masks are certainly not similarly adequate to observe the CA since some masks may turn out to hide the region where the global optimum really takes place. Thus, it is important to find the best mask among the $C_8^{l_m}$ possibilities. This approach does not defer the combinatory explosion on the mask search. As shown in [1], this new way

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of observation trims the problem before actually searching for a more precise solution. We explain in the next section how to automate the search of a good mask and how to have the best "intrinsically emerged" one.

3. HOW TO EVOLVE THE MASK: THE GENETIC EMERGENCE ALGORITHM (GEA)

The mask constitutes a macro observable of the system, abstracting or skipping unnecessary details during some periods of the optimisation process. The algorithm below presents the complete process. The mask is submitted to the evolutionary operations following the feedback of the system: it is selected by the system itself, and the best one will intrinsically emerge with no need for human intervention. In comparison with [1], the improvement proposed in this paper consists in obtaining the best mask, no anymore by random trials, but by the same evolutionary process as the one searching for the optimal rule table.

To evolve the mask, a given population of corresponding masking rules is evolved and the fitness of the mask is evaluated by computing the fitness of the rules set obtained under this masking condition. After given iterations both the mask and the population of the best rules obtained with this mask are memorized in order to start a new set of simulations in which the complete coding (i.e. we take back the 8 neighbours) of the cell states and the rules are re-established. The following pseudo code describes the working of our GEA into three sequential steps:

- **The initialisation phase:**

```
RULES_POP: RANDOM INIT
CA: RANDOM INIT OF VARIETY OF CA CELLS
MASK_POP: RANDOM INIT
```

- **The masking phase:** a mask population is evolved. To perform this task, each mask has to be evaluated by evolving the corresponding masked rules population,

```
FOR tm = 0 TO g_m
   FOR i = 0 TO s_m
      MASK_RULES_POP: RULES_POP+MASK_POP[i]
      FOR tmr - 0 TO g_mr
         FOR j = 0 to s_r
            EVALUATE MASK_RULES_POP[j]
         ENDFOR
         SELECT BEST HALF MASK_RULES_POP
         GENERATE NEW MASK_RULES_POP
      ENDFOR
      EVALUATE MASK_POP[i]
      SAVE TMPBESTMASK_RULES_POP
   ENDFOR
   SELECT BEST HALF MASK_POP
   SAVE BESTMASK_RULES_POP
   GENERATE NEW MASK_POP
ENDFOR

RULES_POP: SAVE BESTMASK_RULES_POP
```

- **The classical phase:** using the best masked rules set, a new unmasked rules population is built. This population is then evolved by a classical GA.

```
FOR tr = 0 TO g_r
   FOR k = 0 to s_r
      FOR m PROBLEM
         EVALUATE RULES_POP[k] ON CA
      ENDFOR
   ENDFOR
   SELECT BEST HALF MASK_RULES_POP
   GENERATE NEW MASK_RULES_POP
ENDFOR
```

4. CONCLUSIONS

In this work, we have examined in more details the concept of "intrinsic emergence" from an engineering point of view. To do so, how to find a good CA implementation of a binary adder is the problem that has been chosen. To solve this problem, a classical GA can be used. However, this choice does not give good results due to the large size of the search space. As it was shown in [1], "intrinsic emergence" can be helpful to improve the classical GA.

A macro observable, a mask, represents then the intrinsic emergent property. By evolving the mask, the machine observer is fullfilled: this is the foundation of the main subject of this paper, the GEA. Indeed, added to a GA, we obtain a coevolution mechanism which is an improvement of the classical evolution strategy.

In order to verify in a fair way the average benefit in time and in fitness offered by GEA, the results need to be compared to a GA running without any mask. The motivations behind each choice of parameter sets are: **1)** How do GEA and GA react for a few number of iterations ? **2)** Being sure to test nearly all mask possibilities, what is the benefit of GEA ? **3)** Does the GEA confirm its improvement for a greater number of iterations even if the search in mask space is too long for the cardinality of the mask space ? **4)** Proper use of the evolutionary strategy on mask, is the GEA more powerful than the GA ? The results obtained through these 4 experiment sets confirm the improvement of this new approach : a gain about 20% in time or in fitness for all non-uniform cases. So, making intrinsic system emergent property is a good way to reduce the search space and to boost the adaptative capacity of the CA population.

This work is a first practical interest of the "intrinsic emergence", and a lot of future work remains to be done. The concept of macro-observables could be extended to other kind of multi-agent systems and more generally to all optimisation problems. This will permit a true generalisation of the GEA and a starting point to a theoretical formalisation of the algorithm. Other ideas such as incremental masking or heteregeneous masking could be also interesting to test. But all these works must test this concept through a larger space of problems. By doing so, we will be able to better understand the subjacent basis of the discussed concept and the effect of the parameters on the efficiency of GEA.

5. REFERENCES

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