Immune Approaches to Experience Acquisition in Time Dependent Optimization

Alessio Gaspar (gaspar@nessie.essi.fr) **Philippe Collard** (Philippe.Collard@i3s.unice.fr)

I3S Laboratory, 2000 Rte des Lucioles, BP121, 06903 Sophia Antipolis (France)
Please refer to http:www.essi.fr:~gaspar/alife.html for a detailed version of this paper.

This paper investigates the relevance of the immune system metaphor to Time Dependent Optimization (TDO). The main feature of immune approaches is their immunization capability. In Time Dependent Optimization, this could help to memorize previously encountered optima in order to improve robustness when facing them again. This paper proposes two simple models of artificial Immune Systems and discuss their immunization ability.

1 A Simple Artificial Immune Systems: Sais

Sais starts with an initial random population of λ bits long strings (B-Cells) and then iterates the 3 following steps:

Evaluation Phase

At first, we compute the *Exogenic Activation* of all B-Cells as follows: $\alpha^i_{ex} = \lambda - \delta_h(B_i, O^t)$. Where i refers to the i^{th} B-Cell of the population, O^t to the optimum at time t, and δ_h to the Hamming distance between them. The B-Cells with a low α_{ex} are not suited to the current environment. We compute their *Endogenic Activation* as follows: $\alpha^i_{en} = ((1/N_s) - d_i) + 1$ where N_s is the number of different types of B-Cells in the population and d_i the density of the i^{th} B-Cell of the population.

The key idea is to distinguish exoactivated B-Cells (immediately useful) to endoactivated ones (potentially useful in a cyclic environment). The former are used for exploring further in the interesting directions while the latter are preserved with equal chances.

Clonal Selection Phase

This phase clones the best elements in order to generate a population P_{ex} by K-Tournament selection of the most exoactivated B-Cells. Then, a so-called *Somatic Hypermutation* mechanism is applied in order to mutate these offsprings. Since the resulting mutants are only kept if they improve their own α_{ex} value, this operator is similar to a local search. Similarly, we generate P_{en} from K-Tournament selection of endoactivated B-Cells. No mutation is performed since the primary objective is their preservation.

Recruitment Phase

We regenerate a population P by reintroducing worthy B-Cells from both P_{ex} and P_{en}. The B-Cells from P_{en} replace directly the endoactivated ones in P while the Exoactivated ones from P and P_{ex} undergo a K-Tournament.

2 Preliminary Experiments

We compared Sais to 5 well known evolutionary algorithms (SGA, Larmarckian Local Search, Random Immigrant, Hypermutation, MicroGA) on a Pattern Tracking problem ($\lambda = 40$). The optimum was replaced every 50 generations by another one randomly located at an increasing Hamming distance (5, then 10 and so on up to λ). The efficiency has been evaluated both by the level of fitness achieved (Reactiveness) and inversely to the depth of the drop off at each transition (Robustness). The results, averaged over 200 experiments, revealed that Sais was less reactive than a SGA coupled to a lamarckian local search operator. A closer examination of these results suggested that, correctly settled, Sais uses less evaluations to reach a quasi-equivalent efficiency in comparison to the Local Search GA. This has been confirmed by further studying the effect of varying the number of clones generated during Phase 2 and comparing the number of evaluations realized by Sais and the Local Search GA. When compared to Culberson's GIGA, Sais revealed to realize a tradeoff between preserving the diversity and converging.

Moreover, as the transitions became more difficult, the robustness improved. We interpreted this observation as a sign of undergoing immunization: as the distance between consecutive optima increases, the new ones have more chances to be close to the previous ones. Further experiments conducted on a Cyclic Pattern Tracking (CPT) with 42 bits long strings and 3 successive optima, confirmed Sais' immunization capability.

2.1 Discussion

The Cyclic Pattern Tracking (CPT) featured 3 successive optima: 100, 010 and 001 (each digit standing for 14 bits). On single experiments, Sais kept previously encountered optima for long times thus featuring a perfect robustness when they occurred again. On average, the system proved to be somewhat unreliable as the densities of the memorized optima underwent a rocky dynamics which led occasionally to "catastrophic forgetting" phenomena. Further experiments revealed that increasing the number of optima deteriorates the immunization ability. Consequently, while

being a robust and reactive approach to TDO, Sais fails to provide a strong immunization capability.

3 Yet Another Sais: YaSais

In order to improve the immunization reliability, YaSais replaces the endoactivation mechanism previously used. It explicitly defines G groups of B-Cells (*Gatherings*) in the population. These are meant to act as macro individuals memorizing previous optima.

Practically, $\mathcal{G}$ B-Cells are exoactivated and processed exactly as in Sais but no endoactivation mechanism is used. A simple permutation ensures that only one B-Cell is exoactivated *per gathering*. Therefore, $\mathcal{G}$ gatherings in a population of size n should enable the memorization of $n/\mathcal{G}$ optima (one in each).

3.1 Preliminary Results

When compared to Sais on the previous Pattern Tracking Problem, YaSais featured a globally equivalent reactiveness and an improved robustness. The parameter $\mathcal{G}$ which both represents the number of gatherings and exoactivated B-Cells, turned out to play an essential role in YaSais' efficiency. Varying this parameter revealed that increasing its value deteriorates the immunization dynamics which is still not perfect despite of the improvement achieved.

3.2 Taking a closer look to the immunization process

We examined the density of the second optimum of the cycle in a single run of YaSais with 5 gatherings of 8 B-Cells. As soon as the optimum 2 was replaced, its density decreased abruptly and then decreased again at each following transition suggesting that its instances were being used to find new optima *via* local search. We took a closer look at one particular transition: 6 instances of the previous optima lost, 6 new optima appeared.

Indeed, the previous optima enabled the local search to find quicker the new ones because of the small Hamming distance that separated them from each other. In our CPT, the n optima were determined by shifting of λ/n positions from left to right a block of λ/n '1'. Consequently, each optimum was only two blocks away from the others. With $n = 5$ and $\lambda = 50$, their Hamming distance was only 20. Consequently, YaSais systematically exoactivated in priority the B-Cells located at this distance (or below) from the new optimum.

We looked again at this particular transition and counted 17 optima (previous or current) in the population. How many of the 23 remaining individuals could be closer to an arbitrary new optimum ? Assuming they are random, the probability of having such a random string located at a Hamming distance inferior or equal to 20 from the optimum is: $P = \sum_{d=0}^{20} 0.5^{50}.C_{\lambda}^{d}$ (approximatively 10% here). Therefore, only 3 individuals among the 23 remaining may be, on average, closer to the new optimum than the B-Cells encoding a previous one. As we are going to exoactivate 8 individuals (one per gathering), this means that if these 3 ones are selected, then 5 other B-Cells encoding a previous optimum will also be used by the local search to reconverge toward the new one. This is coherent with the fact that 6 B-Cells were used that way in our experiment.

3.3 Influence of the Distance between Optima

Therefore, if two optima are close enough, one is used to reach the other. The global performance is kept acceptable because when their distance is short, the previous optima are lost but the consequences on the fitness drop off are limited. On the other hand, if the distance is large, the consequences could be more harmful but in this case the immunization seems to work fine.

In order to check this hypothesis, we used a CPT with only two optima and varied their distance to each other. The results confirmed that increasing their distance improves the immunization ability. Indeed, for low distances, the system systematically looses track of the optima while for higher distances, the densities are maintained over time. The experiments also revealed that for a distance superior to 16 the immunization was fully effective when dealing with two optima. We think that this limit value characterizes the domain of efficiency of the immunization mechanism proposed in this paper.

4 Conclusion

This paper investigated two simple artificial immune systems on TDO and reported their encouraging reactiveness, robustness and immunization capabilities. Concerning the latter, YaSais featured a quasi-optimal strategy. While the random diversity preserved guaranteed robustness on easy transitions, the memory of previous optima was exploited during harder ones. Future work will first concern the generalization of these results on epistasic landscapes that should challenge the usefulness of the local search operator.

References

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