Adaptive Parameterization of Evolutionary Algorithms and Chaotic Artificial Populations

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ABSTRACT: running a genetic algorithm entails setting a number of parameter values. Finding settings that work well on one problem is not a trivial task and a genetic algorithm performance can be severely impacted. Moreover we know that in natural environments population sizes, reproduction and competition rates, change and tend to stabilise around appropriate values according to some environmental factors. This paper deals with a new technique for setting the genetic parameters during the course of a run by *adapting* the population size and the operators rates on the basis of the environmental constrain of maximum population size. In addition genetic operators are seen as alternative reproduction strategies and fighting among individuals is introduced. The algorithm is a particular instance of a chaotic map similar to the logistic map

Introduction

We know, Roughgarden (1979) and Song (1988), that in natural environments population sizes of species, together with their reproduction and competition rates, change and tend to stabilise around appropriate values according to some factors such as natural resources and carrying capacity of the ecosystem.
Unfortunately in standard genetic algorithms, Holland (1975), Goldberg (1989), these features, like population size, crossover and mutation probabilities, are stuck, from generation to generation, on a priori defined values. It means that running such an algorithm entails setting the values of such parameters. Finding settings that work well on one problem is not a trivial task; if poor settings are used, a genetic algorithm performance can be severely impacted. It is clear that in this situation we actually have to deal with two optimization problems : the problem itself and the setting of the GA parameters. Furthermore, the reduction of the number of external parameters of a GA can be seen as a first step towards achieving a problem-dependent self-adaptation of the algorithm.
The idea that one should adapt one's genetic algorithm during the course of a run is not a new one and the reader interested in related work can refer to Annunziato and Pizzuti (2000).
Within this framework the proposed paper deals with a new solution for dynamically setting the parameters of genetic algorithms during the course of a run. The main feature of our methodology is variable population size based on free interaction among individuals. To implement such a feature we reconsidered some basic concepts.
First we reviewed the traditional concept of selection in GAs versus that of direct competition among individuals. Second the two classical genetic operators, crossover and mutation, are viewed not so strictly genetic but, in a little more evolutionary way, like two different ways of reproducing. In this context, as proposed in Jefferson (1995), the metaphor for crossover, mutation and chromosome moves towards *bisexual reproduction*, *mono-sexual reproduction* and *individual* and the general underlying idea is that of moving from the genetic level towards that of artificial evolution of societies and artificial life. On the base of population size we define reproduction and competition rates. Obviously since population size is variable then such rates are variable too. Reproduction probabilities are defined on the basis of the environmental availability of finite natural resources. Roughly speaking we say that the higher the population size is and the less the resources are. It means that, because of the lack of resources, as the population size increases the competition rate gets higher and the reproduction probabilities decrease.
The algorithm is a particular instance of a chaotic map which generalize the well known logistic map. We call such a map '*quadratic-logistic*' and theoretical features have been invetigated. Moreover experimental tests have been curried out on common instances of the travelling salesman problem (TSP). We wish to underline that the aim of our work is not a study of such a problem, we used this benchmark only to provide individuals with a fitness criterion to show the effectiveness of the proposed methodology to solve optimization problems and to compare theoretical results to experimental tests.

From Genetics towards chaotic Evolution of artificial populations

What we propose is an evolutionary algorithm with the goal not to recreate nature as it is, but to move from classical genetic algorithms towards chaotic artificial evolution of populations composed by individuals able to meet and interact. As proposed also by Michalewicz (1994) population size increase is obtained only by reproduction events and all individuals have equal chance of being chosen. In this context when two individuals meet then they can interact in two ways : by reproducing (bisexual reproduction) or by fighting for natural resources (the stronger kills the weaker), otherwise the current individual can differentiate (mono-sexual reproduction). Like in standard GAs all these features are probabilistic, the difference is that probabilities are adaptive instead of being a priori fixed. The main environmental constrain driving the adaptation mechanism is the maximum population size, namely the resources of the ecosystem, and it is the only parameter to be set. Figure 1 shows how the algorithm behaves.

adaptation rules

The main feature of our algorithm is the adaptability of the parameters. Population size is limited by the environmental limit and its dynamics are determined by the reproduction and competition rules among individuals. These two adaptive rates are defined as :

$$Pr = 1 - \frac{N(t)}{Mp} \qquad [1]$$

where Pr is the reproduction rate, N(t) is the current population size, at time t, and Mp is the maximum population size.

$$Pc = 1 - Pr \qquad [2]$$

where Pc is the competition rate and Pr is the reproduction rate.

Roughly speaking we are imposing the rule that if the population density is low then the reproduction rate is high and the competition rate is low. Vice versa, because of the lack of environmental resources, the competition rate gets higher and the reproduction rate decreases.

Selection and meeting

In classic Genetic Algorithms, before crossover, the selection stage is performed, Holland (1975). This step is meant to model the natural feature that the fitter an individual is and the higher the probability to survive is. In the traditional approach this is implemented as a roulette wheel with slots weighted in proportion to the fitness values of the individuals. Through such a wheel a linear search is performed Goldberg (1989) or an intermediate population Whitley (1993) is created.

In our evolutionary algorithm we replaced this stage with the meeting concept. At each iteration we pick the i^{th} individual of the population, for *i* from 1 to population size, up and then we randomly look for a second individual.

The meeting probability is thus defined as the population density

$$Pm = \frac{N(t)}{Mp} \qquad [3]$$

where N(t) is the current population size, at time t, and Mp is the maximum population size.

If someone is met then interaction will start, else mono-sexual reproduction of the current individual might occur.

In this way everyone has a chance of mating and bio-diversity is enhanced, computational time is reduced because the O(*n*), where *n* is the population size, selection routine based on roulette wheel is removed and memory is saved because the intermediate population is not needed anymore.

Crossover and biSexual Reproduction

Crossover is that operator which allows two chromosomes to mutually exchange their genetic equipment giving rise to new sons. In traditional Genetic Algorithms when two chromosome meet then mating is performed with a probability a priori defined. If it happened then the two offsprings resulting from the crossover operator would replace their parents, for instance if they were fitter, in the population, else nothing happens and both originals individuals would survive in the population. This mechanism insures the population size to be constant.

The modification we introduce moves towards bi*sexual reproduction*: mating is performed according to the adaptive rate *Pr* [1], and if it occurred then the resulting sons would not replace their parents, they would simply be added to the population. In this situation population increases of two new elements.

This is much more natural than the genetic crossover because when two individuals mate and have sons these, generally, do not kill their parents as they bear. When the population reaches its maximum limit then reproduction gets destructive in the sense that sons will replace their parents if fitter. This ensures, although this limit, the evolution of the specie.

Competition

Competition starts according to the adaptive rate *Pc* [2]. It means that when two individuals meet and they do not mate then they fight for survival, the stronger kills the weaker and this one is kicked from the population off. This is essential to let the population not to explode in size because in this way the population size decreases of one unit.
This simple strategy mimics in a more nature-like way than the "roulette wheel selection" the evolutionary concept of the *survival of the fittest* because we leave the environment to determine the survivals.

Mutation and mono-sexual Reproduction

Traditionally mutation is that operator which gets one chromosome and randomly changes the alleles of one or more genes. Generally this operator is performed with a probability a priori defined and if it occurred then the mutated chromosome would replace the original one. In this case the population size is preserved because the new solution destroys the original one.
Another point of view is that of considering mutation as non-destructive moving towards the concept of *mono-sexual* reproduction. It is performed according to the adaptive reproduction rate *Pr* [1] and when it occurs an individual first clones itself and then mutates. The mutated individual doesn't replace the original one, it is simply added to the population and the population size increases of one unit. Like bisexual reproduction when population reaches its maximum value then we perform mutation by replacing the original individual with the mutated one if fitter.

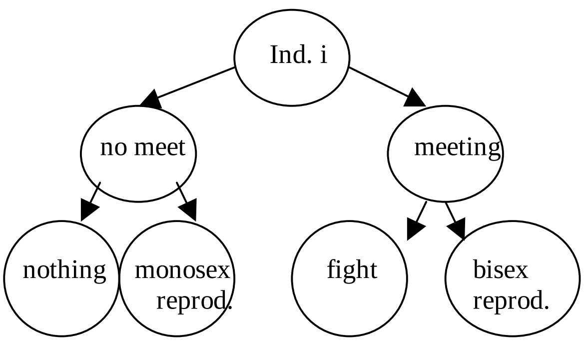

Figure 1. Algorithm

At the edge of chaos : the 'quadratic-logistic map'

The formula underlying our algorithm which describes the population grow rate, see figure 1, is defined in such a way :

$$N(t+1) = N(t) + 2P_mP_rN(t) - P_m(1-P_r)N(t) + (1 - P_m)\, P_r\, N(t) \quad [4]$$

Where N(t+1), N(t) are the population size at time t+1, t, P_m is the meeting probability [3], P_r is the reproduction probability [1]. The term $2P_mP_rN(t)$ refers to the bisexual reproduction step, $P_m(1-P_r)N(t)$ refers to the competition stage and $(1 - P_m)N(t)P_r$ refers to mono-sexual reproduction case. By developing the calculations then [4] reduces to

$$N(t+1) = 2N(t)\left(1 - \left(\frac{N(t)}{Mp}\right)^2\right) \quad [5]$$

Where Mp is the maximum population size. Dividing [5] with Mp then we get

$$X(t+1) = 2X(t)(1 - X(t)^2) \quad [6]$$

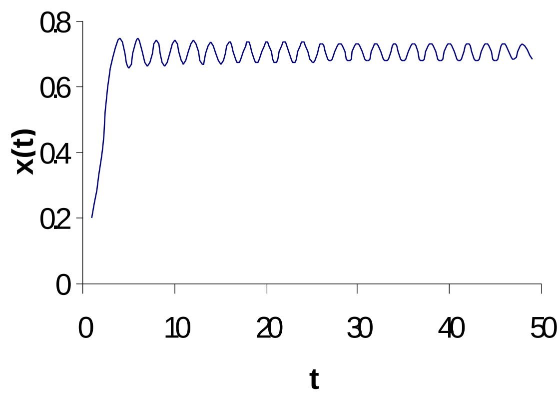

Figure 2. Theoretical behaviour of population dynamics according to equation [6]

Formula [6] can generalized in the following way.

$$X(t+1) = aX(t)(1 - X(t)^2) \quad [7]$$

We wish to underline the similarity of this equation with the well known logistic map which is a simplified model for the variations in the population of insects, May (1976), Ott (1993).

$$X(t+1) = aX(t)(1 - X(t)) \quad [8]$$

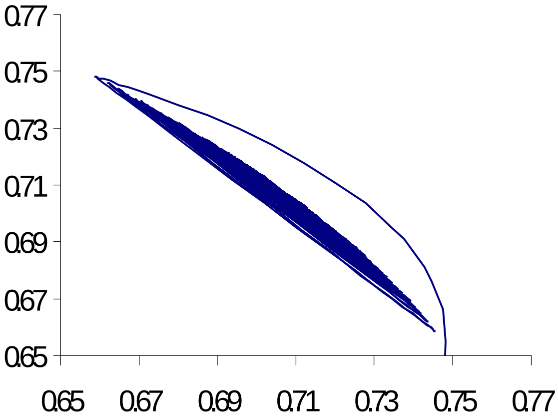

Figure 3. Attractor of equation [6]

In both equations by varying the parameter a we get different chaotic regimes. In particular in the following figures different regimes of [7] for a=2.1, a=2.6 and a=3 are shown. For 1.7<a<2.1 the regime is that of figures 2,3, for a<1.7 the behaviour is not chaotic because in such situations the population dynamics is monotonically decreasing and the attractor is a straight line.

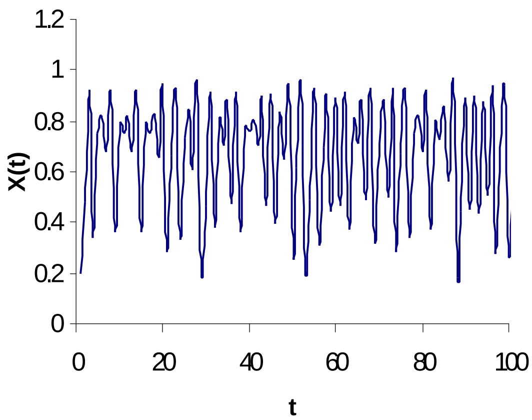

Figure 4. Theoretical behaviour of population dynamics according to equation [7] for a=2.1

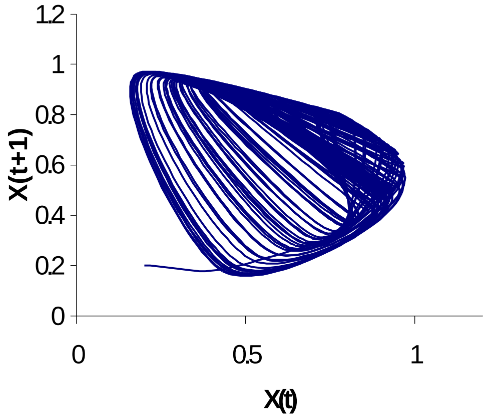

Figure 5. Attractor of equation [7] for a=2.1

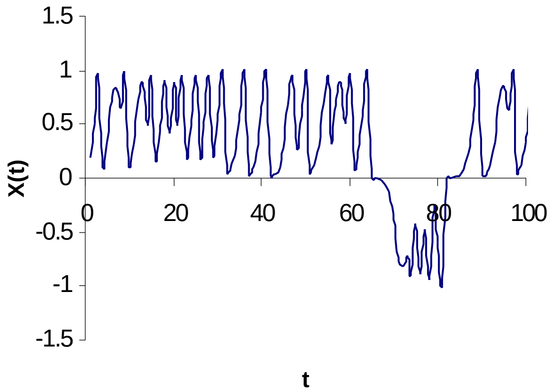

Figure 6. Theoretical behaviour of population dynamics according to equation [7] for a=2.6

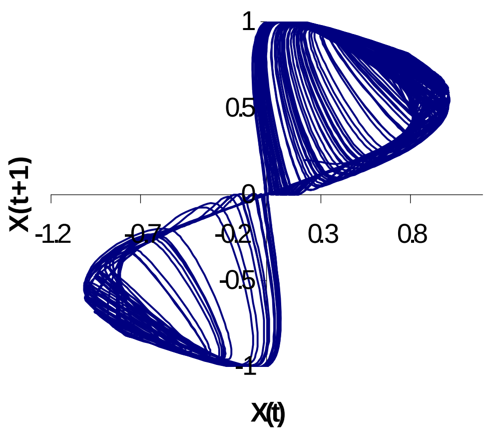

Figure7. Attractor of equation [7] for a=2.6

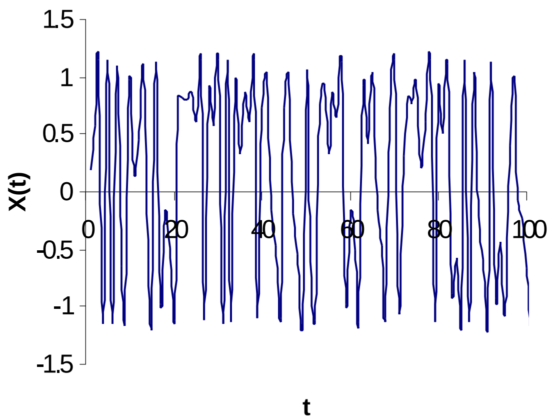

Figure 8. Theoretical behaviour of population dynamics according to equation [7] for a=3

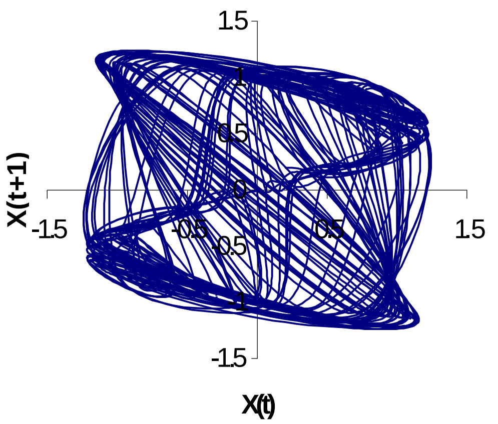

Figure 9. Attractor of equation [7] for a=3

Finally we wish to close this section remarking the main differences with the related work of the last fifteen years.
The introduction of competition is maybe the most relevant one. In fact it allows us to replace the classic genetic selection stage, Holland (1975), Goldberg (1989), with the new meeting concept and selection is left to the environmental dynamics. Individuals die only because of fighting without ageing (Michalewicz (1994)). Population size is not constrained by any resizing scheme, Costa (1999), it is freely determined by the balance of the underlying environmental interactions (reproduction and competition).
Adaptation rules of the operators are driven by population density within an environment with finite natural resources.

Experimental Results : The Travelling Salesman Problem

The Travelling Salesman Problem (TSP) is one of the most famous and studied problems. Its formulation is: “given *n* towns find the minimal tour such that each town, except the first, is visited exactly once”. It is known to be a NP hard problem and it is often used as benchmark for algorithms and approaches. In the following paragraphs we describe how the genetic features of our algorithm have been customized to solve TSP. We wish to underline that we did not use the best operators for this problem because our task is not that of studying this specific problem, we are only interested in demonstrating the effectiveness of our approach to solve optimization problems and in providing a fitness criterion to allow us to analyse the dynamics of the algorithm.
The reader interested in the implementation details can refer to Annunziato and Pizzuti (2000).
In the following part we report the experimental results we curried out on three classical problems, see Reinelt, Oliver (1987), Eilon (1969), : Oliver30 (30 towns), Eilon51(50 towns) and Eilon76(75 towns).
The following tables compare the experimental results of best known real and integer, in brackets, solutions with different techniques and show results on the average behaviour of the adaptive parameters.

TOWNS	GREEDY	SIMPLE G.A.
30	**473.32 (469)**	**425.94 (423)**
50	**505.77 (503)**	**443.98 (441)**
75	**612.65 (605)**	**568.95 (563)**

Table 1. Comparisons of the best results among different strategies

TOWNS	ADAPTIVE E.A.	BEST KNOWN
30	423.74 (420)	423.74 (420)
50	**428.98 (427)**	427.86 (425)
75	**553.16 (546)**	542.31 (535)

Table 2. Comparisons of the best results among different strategies

From these tables it is possible to notice that the Adaptive EA performs pretty well. The solutions found are very close to the best ones, the worst performance is that of 75 towns in which it is achieved a result which is about 4% worse than the best. Moreover we wish to remark the comparison with the simple genetic algorithm because it has been curried out using the same implementation of the operators used for the adaptive strategy. From this comparison it is clear the improvement of the solutions found.

Max Pop. Size	1000	3000	5000	7000	10000
Average pop. size	730	2189	3643	5087	7293
density	0.73	0.729	0.729	0.727	0.729

Table 3. Average results on population size

Max Pop. Size	1000	3000	5000	7000	10000
Bisexual rate (%)	30.43	30.4	31.03	31.7	30.96
Monosex rate (%)	9.68	9.67	9.52	9.28	9.58
Compet. rate (%)	40.07	40.06	40.53	40.98	40.52

Table 4. Average results of the adaptive rates as function of the max population size

From these two tables one remark is needed. From table II we can notice that the population density, defined as the ratio between the average and the maximum population size, is almost constant and it ranges in the interval 0.727-0.73. This value can be considered, see also figure 5, the equilibrium point around which the population oscillates. This result is of particular interest because it represents the *natural* constant balance of the different interactions, reproduction and competition, of individuals dealing with finite environmental resources. Moreover the equilibrium point tends to the average, as in the theoretical case of equation [6], and the experimental dynamics are very similar to those expected in figure 2. The slight differences can be ascribed to the random generator. From table 4 and the following figure we can notice the same behaviour. All the parameters tend to stabilize near an equilibrium point, the average value, around which they oscillate.

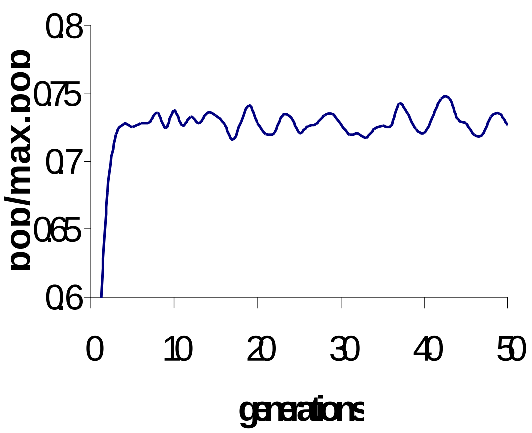

Figure10. Example of density population dynamics

Finally we have to say that the equilibrium points around which the parameters tend to stabilize are not dependent on the initial population size which is randomly chosen. Further results can be found in Annunziato and Pizzuti (2000).

Conclusions and future work

In this paper we curried out a study with the aim of moving towards simulations of chaotic evolution of artificial societies without external parameter settings. The key idea of the proposed strategy is the concept of adaptive parameterisation driven by the concept of finite resources of the environment, namely the maximum population size the ecosystem can sustain.
To achieve this task the classic genetic operators, crossover and mutation, are seen as two different ways of generating new sons, without replacing the parents, and real competition among individuals is introduced.
Dynamic population, obviously, removes the constrain of population size. This is important because such a parameter is the most studied and the one that mainly affects the result of traditional genetic algorithms. In the proposed approach population size is determined at each generation by the balance between reproduction and competition.
The algorithm is the implementation of a particular instance of a chaotic map similar to the well known logistic map. Theoretical regimes of the map have been investigated and compared to experimental tests. Such experimentations have shown the effectiveness of the adaptive EA to solve optimization problems and confirmed the theoretical expectation.
The lines of research for future work are basically two. The first is that one which stresses the simulation of natural evolution, introducing sex and age, and different adaptive rules can be studied. Moreover it is possible to go further by introducing artificial life concepts. For instance physical space can be introduced and adaptive rates, instead of being global environmental parameters, can be defined inside the individuals as endogenous features (Bäck, 1992).
The second line of research might be focused on the implementation of the highly chaotic regimes of equation [7].

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