Parameter-Less Optimization with the Extended Compact Genetic Algorithm and Iterated Local Search

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Abstract. This paper presents a parameter-less optimization framework that uses the extended compact genetic algorithm (ECGA) and iterated local search (ILS), but is not restricted to these algorithms. The presented optimization algorithm (ILS+ECGA) comes as an extension of the parameter-less genetic algorithm (GA), where the parameters of a selecto-recombinative GA are eliminated. The approach that we propose is tested on several well known problems. In the absence of domain knowledge, it is shown that ILS+ECGA is a robust and easy-to-use optimization method.

1 Introduction

One of the major topics of discussion within the evolutionary computation community has been the parameter specification of the evolutionary algorithms (EAs). After choosing the encoding and the operators to use, the EA user needs to specify a number of parameters that have little to do with the problem (from the user perspective), but more with the EA mechanics itself. In order to release the user from the task of setting and tuning the EA parameters, several techniques have been proposed. One of these techniques is the parameter-less GA, which controls the parameters of a selecto-recombinative GA. This technique can be applied to various types of (selecto-recombinative) GAs, and in conjunction with a high-order estimation of distribution algorithm (EDA), such as the extended compact GA (ECGA) [1] or the Bayesian optimization algorithm (BOA) [2], results in a powerful and easy-to-use search algorithm. Multivariate EDAs have shown to outperform the simple GA (SGA) by several orders of magnitude, especially on very difficult problems. However, these advanced search algorithms don't come for free, requiring more computational effort than the SGA when moving from population to population. In many problems this extra effort is well worth it, but for other (less complex) problems, a simpler algorithm can easily outperform a multivariate EDA.

Typical EAs are based on two variation operators: recombination and mutation. Recombination and mutation search the solution space in different ways and with different resources. While recombination needs large populations to

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combine effectively the necessary information, mutation works best when applied to small populations during a large number of generations. Spears [3] did a comparative study between crossover and mutation operators, and theoretically demonstrates that there were some important characteristics of each operator that were not captured by the other.

Based on these observations, we propose a new parameter-less optimization framework, that consists of running two different search models simultaneously. The idea is to use the best of both search strategies in order to obtain an algorithm that works reasonably well in a large class of problems. The first method can be a parameter-less ECGA, based on selection and wise recombination to improve a population of solutions. As a second method we can use an iterated local search (ILS) algorithm with adaptive perturbation strength. Instead of working with a population of solutions, the ILS iterates a single solution by means of selection and mutation. We called optimization framework, instead of optimization algorithm, since what we propose here is not tied up with the ECGA or our ILS implementation. Other algorithms, such as BOA or other ILS implementations, can be considered with similar or better results. However, in this paper we restrict ourselves to the concrete implementation of the ILS+ECGA algorithm and the discussion of the corresponding results.

The next section reviews some of the work done in the topic of EA parameter tuning/control, then describes the parameter-less GA technique, the ECGA, and the ILS framework. Then, Section 3 describes the basic principles of the parameter-less optimization framework and our ILS+ECGA implementation. In Section 4, computational experiments are done to validate the proposed approach. Section 5 highlights some extensions of this work. Finally, in Section 6, a summary and conclusions are presented.

2 Related Work

This section reviews some of the research efforts done in setting and adapting the EAs parameters, describes the parameter-less GA technique and the mechanics of the ECGA and ILS.

2.1 Parameter Tuning and Parameter Control in EAs

Parameter tuning in EAs involves the empirical and theoretical studies done to find optimal settings and understand the interactions between the various parameters. An example of that was the work of De Jong [4], where various combinations of parameters were tested on a set of five functions. On those experiments, De Jong verified that the parameters that gave better overall performance were: population size in the range 50-100, crossover probability of 0.6, mutation probability of 0.001, and generation gap of 1.0 (full replacement of the population in each generation). Some other empirical studies have been conducted on a larger set of problems yielding somewhat similar results [5,6]. Almost 30 years later, these parameters are still known as the “standard” parameters, being sometimes incorrectly applied to many problems. Besides these empirical studies, some work was done to analyze the effect of one or two parameters in isolation, ignoring the others. Among the most relevant studies, are the ones done on selection [7], population sizing [8,9], mutation [10,11], and control maps [12,13]. The work on population sizing is of special relevance, showing that setting the population size to 50-100 for all problems is a mistake. The control maps study gave regions of the parameter space (selection and crossover values) where the GA was expected to work well, under the assumption of proper linkage identification.

In parameter control we are interested in adapting the parameters during the EA run. Parameter control techniques can be subdivided in three types: deterministic, adaptive, and self-adaptive [14]. In deterministic control, the parameters are changed according to deterministic rules without using any feedback from the search. The adaptive control takes place when there is some form of feedback that influences the parameter specification. Examples of adaptive control are the works of Davis [15], Julstrom [16], and Smith & Smuda [17]. The parameter-less GA technique is a mix of deterministic and adaptive rules of control, as we will see in the next section. Finally, self-adaptive control is based on the idea that evolution can be also applied in the search for good parameter values. In this type of control, the operator probabilities are encoded together with the corresponding solution, and undergo recombination and mutation. This way, the best parameter values will tend to survive because they originate better solutions. Self-adaptive evolution strategies (ESs) [18] are an example of the application of this type of parameter control.

2.2 Parameter-Less Genetic Algorithm

The parameter-less genetic algorithm [19] is a technique that eliminates the parameters of a selecto-recombinative GA. Based on the schema theorem [20] and various facet-wise theoretical studies of GAs [9,12], Harik & Lobo automated the specification of the selection pressure (s), crossover rate (p_c), and population size (N) parameters.

The selection pressure and crossover rate are set to fixed values, according to a simplification of the schema theorem in order to ensure the growth of promising building blocks. Simplifying the schema theorem, and under the conservative hypothesis that a schema is destroyed during the crossover operation, the growth ratio of a schema can be expressed by $s\,(1-p_c)$. Thus, setting $s = 4$ and $p_c = 0.5$, gives a net growth factor of 2, ensuring that the necessary building blocks will grow. If these building blocks will be able to mix in a single individual or not is now a matter of having the right population size.

In order to achieve the right population size, multiple populations with different sizes are run in a concurrent way. The GA starts by firing the first population, with size $N_1 = 4$, and whenever a new population is created its size is doubled. The parameter-less GA gives an advantage to smaller populations by giving them more function evaluations. Consequently, the smaller populations have the chance to converge faster than the large ones. The reader is referred to Harik & Lobo [19] for details on this approach.

***Extended Compact Genetic Algorithm* (ECGA)**

(1) Create a random population of N individuals.
(2) Apply selection.
(3) Model the population using a greedy MPM search.
(4) Generate a new population according to the MPM found in step 3.
(5) If stopping criteria is not satisfied, return to step 2.

Fig. 1. Steps of the extended compact genetic algorithm (ECGA).

2.3 Extended Compact Genetic Algorithm

The extended compact genetic algorithm (ECGA) [1] is based on the idea that the choice of a good probability distribution is equivalent to linkage learning. The ECGA uses a product of marginal distributions on a partition of the decision variables. These kind of probability distributions are a class of probability models known as marginal product models (MPMs). The measure of a good MPM is quantified based on the minimum description length (MDL) principle. According to Harik, good distributions are those under which the representation of the distribution using the current encoding, along with the representation of the population compressed under that distribution, is minimal. Formally, the MPM complexity is given by the sum $C_m + C_p$. The model complexity C_m is given by

$$C_m = \log_2(N+1) \sum_i (2^{S_i} - 1), \tag{1}$$

where N is the population size and S_i is the length of the i^{th} subset of genes. The compressed population complexity C_p is quantified by

$$C_p = N \sum_i E(M_i), \tag{2}$$

where $E(M_i)$ is the entropy of the marginal distribution of subset i. Entropy is a measure of the dispersion (or randomness) of a distribution, and is defined as $E = \sum_{j=1}^{n} -p_j \log_2(p_j)$, where p_j is the probability of observing the outcome j in a total of n possible outcomes.

As we can see in Figure 1, steps 3 and 4 of the ECGA differ from the simple GA operation. Instead of applying crossover and mutation, the ECGA searches for a MPM that better represents the current population and then generates a new population sampling from the MPM found in step 3. This way, new individuals are generated without destroying the building blocks.

2.4 Iterated Local Search

The iterated local search (ILS) [21] is a simple and general purpose metaheuristic that iteratively builds a sequence of solutions generated by an embedded heuristic, leading to better solutions than repeated random trials of that

***Iterated Local Search* (ILS)**

```
s_0 = GenerateInitialSolution(seed)
s* = LocalSearch(s_0)
repeat
    s' = Perturbation(s*, history)
    s*' = LocalSearch(s')
    s* = AcceptanceCriterion(s*, s*', history)
until termination condition met
```

Fig. 2. Pseudo-code of Iterated Local Search (ILS).

heuristic. This simple idea is not new, but Lourenço et al. formulated as a general framework. The key idea of ILS is to build a biased randomized walk in the space of local optima, defined by some local search algorithm. This walk is done by iteratively perturbing a locally optimal solution, next applying a local search algorithm to obtain a new locally optimal solution, and finally using an acceptance criterion for deciding from which of these two solutions to continue the search. The perturbation must be strong enough to allow the local search to escape from local optima and explore different areas of the search space, but also weak enough to avoid that the algorithm degenerates into a simple random restart algorithm (that typically performs poorly).

Figure 2 depicts the four components that have to be specified to apply an ILS algorithm. The first one is the procedure `GenerateInitialSolution` that generates an initial solution s_0. The second one is the procedure `LocalSearch` that implements the local search algorithm, giving the mapping from a solution s to a local optimal solution s^*. Any local search algorithm can be used, however, the performance of the ILS algorithm depends strongly on the one chosen. The `Perturbation` is responsible for perturbing the local optima s^*, returning a perturbed solution s'. Finally, the procedure `AcceptanceCriterion` decides which solution (s^* or $s^{*\prime}$) will be perturbed in the next iteration. An important aspect in the perturbation and the acceptance criterion is to introduce a bias between intensification and diversification of the search. Intensification in the search can be reached by applying the perturbation always to the best solution found and using small perturbations. On the other hand, diversification is achieved by accepting every new solution $s^{*\prime}$ and applying large perturbations.

3 Two Search Models, Two Tracks, One Objective

Different approaches have been proposed to combine global search with local search. A common practice is to combine GAs with local search heuristics. It has been used so often that originated a new class of search methods called memetic algorithms [22]. In this work we propose something different, the combination of two global search methods based on distinct principles. By principles we mean variation operators, selection methods, and population management policies. The ECGA is a powerful search algorithm based on recombination to improve solutions, however at the cost of extra computation time (needed to search for a good MPM) in each generation. For hard problems this effort is well worth it, but for other problems, less complex search algorithms may do. This is where ILS comes in. As a light mutation-based algorithm, ILS can quickly and reliably find good solutions for simpler or mutation-tailed problems. What we propose is to run ILS and ECGA simultaneously. This "pseudo-parallelism" is done by giving an equal number of function evaluations to each search method alternately. ILS and ECGA will have their own track in the exploration of the search space, without influencing each other. In the resulting optimization algorithm, that we call ILS+ECGA, the search will be done by alternating between ILS and ECGA.

3.1 Parameter-Less ECGA

The parameter-less GA technique is coupled together with the ECGA. An important aspect of our implementation is the saving of function evaluations. Since the crossover probability is always equal to 0.5, there is no need of reevaluating the individuals that are not sampled from the model. This way, half of the total number of function evaluations are saved.

3.2 ILS with Adaptive Perturbation

In this section we describe the ILS implementation used for this work, and present a simple but effective way to eliminate the need of specifying its parameters. The four components chosen for the ILS algorithm are:

Local Search: next ascent hill climber (NAHC). NAHC consists in having one individual and keep mutating each gene, one at a time, in a predefined random sequence, until the resulting individual is fitter than the original. In that case, the new individual replaces the original and the procedure is repeated until no improvement can be made further.

Initial Solution: randomly generated. Since the NAHC is fast in getting local optima solutions, there is no need to use a special greedy algorithm.

Acceptance Criterion: accept always the last local optima obtained ($s^{*\prime}$) as the solution from where the search will continue. In a way, this is done to compensate the intensive selection criterion from NAHC, where just better solutions are accepted. On the other side, with this kind of acceptance criterion we promote a stochastic search in the space of local optima.

Perturbation: probabilistic and greater than the mutation rate of the NAHC (equal to $1/l$). The perturbation strength is proportional to the problem size (number of genes l). This way, the perturbation is always strong enough, whatever the problem size. Each allele is perturbed with probability $p_p = 0.05l/l = 0.05$. This means that on average 5% of the genes are perturbed. However, if the problem length is too small (for example, $l \leq 60$), then the perturbation becomes of the same order of magnitude than the mutation done by NAHC. To avoid this, we fix the perturbation probability to $3/l$ for problems where $l \leq 60$. This way, we ensure that on average the perturbation strength is at least 3 times greater than the mutation strength of NAHC. This is done to prevent perturbation from being easily cancelled by the local search algorithm. Nevertheless, the perturbation strength may not be strong enough if the attraction area of a specific local optima is too big, leading to a situation where frequently $s^{*\prime} = s^*$. In that case, we need to increase the perturbation strength until we get out from the attraction area of the local optima. Therefore, the perturbation strength α is updated as follows:

$$\alpha_{new} = \begin{cases} \alpha_{current} + 0.02l, & \text{if } s^{*\prime} = s^* \\ 0.05l, & \text{if } s^{*\prime} \neq s^* \end{cases} \tag{3}$$

This way, the updated perturbation probability is equal to α_{new}/l.

3.3 ILS+ECGA

The parameter-less optimization framework proposed consists of running the two different search models more or less simultaneously. This is accomplished by switching back and forth between one method and the other after a predefined number of function evaluations have elapsed ($fe_{elapsed}$). Notice however that there are minimum execution units that must be completed. For example, a generation of the parameter-less ECGA cannot be left half done. Likewise, a NAHC search cannot be interrupted in the middle. Therefore, care must be taken to ensure that both methods receive approximately the same number of evaluations and closest as possible from the defined value. For our experiments we used $fe_{elapsed} = 500$. The ideal $fe_{elapsed}$ would be equal to one, since the computational cost of changing between methods is minimal. However, in practice, it will never happen because of the minimal execution units of the ILS and ECGA. Since the main objective of this work is to propose a parameter-less search method, $fe_{elapsed}$ was fixed to a reasonable value.

Initially, ILS with adaptive perturbation runs during 500 function evaluations, plus the ones needed to finish the current NAHC search. Then, the parameter-less ECGA will run during another 500 evaluations, plus the ones needed to complete the current generation. And the process repeats *ad eternum* until the user is satisfied with the solution quality obtained or run out of time. This approach supplies robustness, small intervention from the user (just the fitness function needs to be specified), and good results in a broad class of problems.

4 Experiments

This section presents computer simulations on five test problems. These problems were carefully chosen to represent different types of problem difficulty. For each problem, the performance of ILS+ECGA algorithm is compared with other four search algorithms: the simple GA with "standard" parameters (SGA1), the simple GA with tuned parameters (SGA2), the ILS with adaptive perturbation alone (ILS), and the parameter-less ECGA alone (ECGA). For the GAs, we use binary encoding, tournament selection, and uniform crossover (except for ECGA). SGA1 represents a typical GA parameter configuration: population size $N = 100$, crossover probability $p_c = 0.6$, mutation probability $p_m = 0.001$, and selection pressure $s = 2$. SGA2 represents a tuned GA parameter configuration. For each problem, the GA parameters were tuned to obtain the best performance. Note that they aren't optimal parameters, but the best parameters found after a period of wise trials[1]. ILS and ECGA are tested alone to compare with ILS+ECGA and understand the advantages of running the two search models simultaneously.

For each problem, 20 independent runs were performed in order to get results with statistical significance. For each run, 2,000,000 function evaluations were allowed to be spent. For each algorithm, the mean and standard deviation of the number of function evaluations spent to find the target solution were calculated. For function optimization testing, each run was considered well succeeded if it found a solution with a function value $f(x_1, \ldots, x_n)$ in a given neighborhood of the optimal function value $f(x_{1opt}, \ldots, x_{nopt})$. The number of runs ($R_{ts}$) in which a target solution was found was also recorded. For each problem, all algorithms started with the same 20 seed numbers in order to avoid initialization (dis)advantages among algorithms.

4.1 Test Functions

The first problem is the onemax function, that simply returns the number of ones in a string. A string length of 100 bits is used. The optimal solution is the string with all ones. After some tuning, SGA2 was set with $N = 30$, $p_c = 0.9$, $p_m = 0.005$, and $s = 2$.

The second test function is the unimodal Himmelblau's function, defined as $f(x_1, x_2) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2$. The search space considered is in the range $0 \leq x_1, x_2 \leq 6$, in which the function has a single minimum at (3,2) with a function value equal to zero. Each variable x_i is encoded with 12 bits, totalizing a 24-bit chromosome. For a successful run, a solution with a function value smaller or equal to 0.001 must be found. After some tuning, SGA2 was set with the parameters $N = 100$, $p_c = 0.9$, $p_m = 0.01$, and $s = 2$.

The third function is the four-peaked Himmelblau's function, defined as $f(x_1, x_2) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2 + 0.1(x_1 - 3)^2(x_2 - 2)^2$. This function is similar to the previous one, but the range is extended to $-6 \leq x_1, x_2 \leq 6$. Since the original Himmelblau's function has four minima in this range (one in each quadrant), the added term causes the point (3,2) to be global minimum. Each variable x_i is encoded with 13 bits, giving a chromosome with 26 bits. Once more, a run is considered successful if the function value is within 0.001 of the global optima. The SGA2 uses $N = 200$, $p_c = 0.5$, $p_m = 1/l$, and $s = 4$.

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[1] These trials were based on the work of Deb & Agrawal [23], since they used the same test functions. For each trial, 5 runs were performed to get some statistical significance.

Table 1. Mean and standard deviation of the number of function evaluations spent to find the target solution for the tested problems. The number of runs (R_{ts}) in which a target solution was found was also recorded.

		SGA1	**SGA2**	**ECGA**	**ILS**	**ILS+ECGA**
Onemax	mean	2,990	1,256	13,735	451	451
	std. dev.	±189	±258	±5,371	±65	±65
	R_{ts}	20	20	20	20	20+0
Unimodal Himmelblau	mean	2,019	1,750	3,731	1,400	3,174
	std. dev.	±790	±497	±2,290	±1,385	±2,766
	R_{ts}	16	20	20	20	14+6
Four-peaked Himmelblau	mean	2,414	2,850	5,205	2,593	4,990
	std. dev.	±750	±668	±2,725	±3,002	±3,432
	R_{ts}	14	20	20	20	12+8
10-variable Rastrigin	mean	1,555,300	570,000	149,635	>2,000,000	275,170
	std. dev.	±306,600	±87,240	±85,608	—	±87,472
	R_{ts}	3	20	20	0	0+20
Bounded Deceptive	mean	—	741,000	15,388	>2,000,000	31,870
	std. dev.	—	±95,416	±3,417	—	±15,306
	R_{ts}	0	20	20	0	0+20

The fourth function tested is the 10-variable Rastrigin's function. This is a massively multimodal function, known to be difficult to any search algorithm. It is defined as $f(x_1, \ldots, x_{10}) = 100 + \sum_{i=1}^{10} x_i^2 - 10\cos(2\pi x_i)$, being each variable defined in the range $-6 \leq x_i \leq 6$. This function has a global minimum at (0,0,...,0) with a function value equal to zero. There are a total of 13^{10} minima, of which 2^{10} are close to the global minimum. A solution with a function value smaller or equal to 0.01 is considered a target solution. For best performance, SGA2 was set to $N =$ 10,000, $p_c = 0.9$, $p_m = 1/l$, and $s = 8$.

The fifth and last problem is a bounded deceptive function, that results from the concatenation of 10 copies of a 4-bit trap function. In a 4-bit trap function the fitness value depends on the number of ones (u) in a 4-bit string. If $u \leq 3$, the fitness is $3 - u$, if $u = 4$, the fitness is equal to 4. The overall fitness is the sum of the 10 independent sub-function values. For such a problem, the SGA is only able to mix the building blocks with very large population sizes. To assure that we find the optimal solution in all 20 runs, the SGA2 was set with $N=$ 60,000, $p_c = 0.5$, $p_m = 0$, and $s = 4$.

4.2 Results

The results obtained can be seen in Table 1. The growing difficulty of the five tested problems can be verified by the number of runs (R_{ts}) in which algorithms found a target solution, and by the number of function evaluations needed to do so. For the onemax problem, all the algorithms found the target solution in the 20 runs. Both ILS and ILS+ECGA got the same (and the best) results. This can be explained because the ILS is the first search method to run (500 function evaluations) in the ILS+ECGA framework. Taking into account that both algorithms used the same seed numbers, it was expected that they did similar since the NAHC always returned the optimal solution in the first time that it was solicited. This eventually happens because the problem is linear in Hamming space. In fact, that's the reason why mutation-based algorithms outperformed the rest of the algorithms for this problem. For the remaining problems, the SGA1 (with "standard" parameters) couldn't find a satisfiable solution in all runs. Although SGA1 performed well for the Himmelblau's functions, it wasn't robust enough to achieve a target solution in all runs. For the 10-variable Rastrigin's function, SGA1 found only 3 good solutions, and for the deceptive function, the "standard" parameter configuration failed completely, converging always to sub-optimal solutions. These results confirmed that setting these parameters to all kind of problems is a mistake.

For the Himmelblau's functions, SGA2 and ILS obtained the best results, taking half of the evaluations spent by ECGA. The ILS+ECGA algorithm, mostly due to the ILS performance, obtained a reasonable performance. Note that ILS was the algorithm responsible for getting a good solution in 14 and 12 (in a total of 20) runs, for unimodal and four-peaked Himmelblau's functions, respectively.

For the 10-variable Rastrigin's function, a different scenario occurred. ILS failed all the attempts to find a satisfiable solution. This is not a surprising result, since search algorithms based on local search don't do well in massively multimodal functions. Remember that some of the components (NAHC and adaptive perturbation scheme) of our ILS implementation were chosen in order to solve linear, non-correlated, or mutation-tailed problems in a quick and reliable way. For other kind of problems, parameter-less ECGA performance is quite good, making ILS+ECGA a robust and easy-to-use search algorithm. The ECGA was the best algorithm for this problem, and because of it, ILS+ECGA got the second best result, taking half of the evaluations of the SGA2.

For the bounded deceptive problem, SGA1 (converged to sub-optimal solutions) and ILS (spent all of the 2,000,000 evaluations available) didn't find the optimal solution. For this problem, the real power of ECGA could be verified. SGA2 took almost 50 more times function evaluations than ECGA to find the best solution in all runs. Taking advantage of the ECGA performance, ILS+ECGA was the second best algorithm, finding the target solution in 2 times more evaluations than the ECGA alone (as expected).

5 Extensions

There are a number of extensions that can be done based on this work:

- investigate other workload strategies;
- investigate interactions between the two search methods;
- investigate how other algorithms perform in the framework.

For many problems, the internal mechanisms needed by the ECGA to build the MPM may contribute to a significant fraction of the total execution time. Therefore, it makes sense (and it's more fair) to divide the workload between the two methods based on total execution time rather than on fitness function evaluations. Another aspect is to investigate interactions between the two methods. How much beneficial is it to insert one (or more) ILS local optimal solution(s) in one (or more) population(s) of the parameter-less ECGA? What about the reverse situation? Finally, other algorithm instances such as BOA could be used instead of the ECGA, as well as other concrete ILS implementation.

We are currently exploring some of these extensions.

6 Summary and Conclusions

This paper presented a concrete implementation of the proposed parameter-less optimization framework that eliminates the need of specifying the configuration parameters, and combines population-based search with iterated local search in a novel way. The user just needs to specify the fitness function in order to achieve good solutions for the optimization problem.

Although the combination might not perform as well as the best algorithm for a specific problem, it is more robust than either method alone, working reasonably well on problems with different characteristics.

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