International Journal of Approximate Reasoning 57 (2015) 40–43

Contents lists available at ScienceDirect

International Journal of Approximate Reasoning

www.elsevier.com/locate/ijar

A note on “Adaptive fuzzy fitness granulation for evolutionary optimization”

Israel Cruz-Vega, Hugo Jair Escalante *

Computer Science Department, Instituto Nacional de Astrofísica, Óptica y Electrónica, Luis Enrique Erro No. 1, Tonantzintla, 72840, Puebla, Mexico

ARTICLE INFO

Article history:
Received 23 August 2014
Received in revised form 25 November 2014
Accepted 25 November 2014
Available online 28 November 2014

Keywords:
Surrogate modeling
Evolutionary algorithms
Granular computing

ABSTRACT

In this note we comment on some aspects of the Adaptive-Fuzzy-Fitness-Granulation (GA-AFFG) process introduced in [1]. We have found methodological inconsistencies that, we think, should be made public to the scientific community.

1. Brief summary of the work under analysis

Akbarzadeh-T et al. describe in [1] a novel approach for surrogate-modeling in evolutionary algorithms called GA-AFFG. This method generates fuzzy granules in the solutions' space increasingly, as the search goes on, where each granule has an associated fitness value. New solutions are compared to existing granules, if a solution is similar enough to a granule, then the fitness of the granule is used as the fitness of the solution; otherwise, the real fitness function of the solution is computed and a new granule is generated. The authors propose a dynamic threshold that increases with the optimization process, making more difficult for solutions to be evaluated with granules at final generations. The authors report results on both benchmark and real (industry) problems.

2. Comments on the work under analysis

We found the ideas proposed in [1] very interesting and useful for both practitioners and researchers on evolutionary computation. However, we also found questionable information and methodological issues that, we think, should be made public to the scientific community in order to correctly understand the actual capabilities of the GA-AFFG method. The rest of this note elaborates on the main inconsistencies[1] we identified.

* Corresponding author. Tel.: +52 222 2663100x8319.
E-mail addresses: iscruz@inaoep.mx (I. Cruz-Vega), hugojair@inaoep.mx (H.J. Escalante).

[1] One should note that the first inconsistency we detected may be debatable: authors take a decision by comparing two quantities of different nature, but they include a scalar (α) that, under some circumstances, can make such quantities comparable, see below. Although this can be considered subjective, in our opinion it is not technically correct to compare quantities that are not comparable at all.

http://dx.doi.org/10.1016/j.ijar.2014.11.006
0888-613X/

$$f\left(X_j^i\right)=\begin{cases} f(C_K) & \text{if} \quad \max\limits_{k\in\{1,2,\dots,l\}}\}\{\bar{\mu}_{j,k}\}>\theta^i \\ f\left(X_j^i\right) & \text{computed by fitness function} \quad \text{otherwise}\end{cases}$$

Fig. 1. Snapshot of the conditional statement for using the surrogate model in [1].

Table 1
Average performance reported in [1] (columns 2 and 3), performance of our implementation of the GA-AFFG method when minimizing the functions (columns 4 and 5), and global optimum known for the benchmark considered in [1].

Function	Perf. reported in [1]		Perf. our implementation		Optimum
	GA	GA-AFFG	GA	GA-AFFG	
F_1: De Jong's 1	78.58	78.47	1.4498E−06	0.72089	0.0
F_2:	72.66	72.11	0.87653	2.3292	–
F_3: Michalewicz	7.85	7.71	−7.8284	−2.63	−9.66
F_4: Rastrigin	62.56	65.76	82.86	156.76	0.0
F_5: Schwefel's	6210.24	6031.67	−5942.5	−1448.7	0.0
F_6: Griewangk's	1643.77	1631.15	64.281	132.14	0.0

We have identified the following inconsistencies:

- The conditional statement for deciding whether solutions should use granules' fitness or the real fitness function equates two quantities of different nature and scale, which makes the conditional to have little sense. Fig. 1 shows a snapshot of the conditional under analysis.
  This conditional compares a quantity derived from the Gaussian similarity between granules and solutions ($\bar{\mu}_{j,k}$) against threshold θ^i which is derived from a formula based on fitness values. Comparing two quantities from different scale/nature is not adequate to determine if a solution should be evaluated using the surrogates (i.e., $f(C_k)$) or the real fitness function (i.e., $f(X_j^i)$). Authors introduce a parameter, α, that scales fitness values in θ^i, nevertheless, still the comparison does not make sense. In order to support our previous statement, we ran the algorithm using the same parameters as specified by the authors in Tables 2 and 3 in [1] and plot the values of θ^i and $\max_{k\in\{1,\dots,l\}}\bar{\mu}_{j,k}$ for the six benchmark functions considered in the study.
  Fig. 2 shows the average values, over 10 runs, of θ^i and $\max_{k\in\{1,\dots,l\}}\bar{\mu}_{j,k}$ when minimizing the different functions considered in the experimental study with a genetic algorithm (the same version of the algorithm as in [1]). Recall the surrogate would be used when θ^i is lower than the other quantity. It can be seen that the behavior of both measures (θ^i and $\max_{k\in\{1,\dots,l\}}\bar{\mu}_{j,k}$) is erratic and the statements from the authors[2] do not hold. In fact, in most of the plots of Fig. 2, θ^i starts at a high value and decreases as generations increase. Clearly, θ^i tends to the value[3] of α when the number of generations tends to infinity, because of the convergence of the genetic algorithm and of the form of θ^i. Hence, whereas one can anticipate the behavior of θ^i (converging to α), the behavior of $\max_{k\in\{1,\dots,l\}}\bar{\mu}_{j,k}$ depends on the problem at hand and the domain for the corresponding variables. Therefore, the conditional statement under analysis is not correct.
  Fig. 3 shows average values, over 10 runs, of the same variables when maximizing the different functions.[4] It can be seen that the behavior of both quantities is even more erratic. Actually, for most functions, the real fitness function would not be used at all (i.e., θ^i is always larger than $\max_{k\in\{1,\dots,l\}}\bar{\mu}_{j,k}$). Therefore, we can conclude that the statements of the authors on the behavior of θ^i, and, consequently, on the usage of the surrogate during the search, do not hold. This is true when facing the benchmark functions as minimization and maximization problems.
- The experimental study on benchmark problems is uninformative as the problems were approached as maximization tasks. In Table 2, in [1], the authors report maximization performance of their method in problems F_1, F_2, F_3, F_5 and F_6. However, it is well know that those functions are minimization problems, this can be verified in textbooks, the references cited by the authors, or even by searching in the Web, see e.g., [2]. In consequence, the observations and conclusions from [1] regarding benchmark functions are not necessarily valid.
  In this context, we show in Table 1 the performance reported by the authors in [1], and the performance obtained by our implementation of GA-AFFG approaching the problems as minimization ones (correct implementation). For reference we also show the known optimum for each function. As expected the performance reported in [1] is far away from the known optima (columns 2 and 3). Nevertheless, the results obtained with our implementation of the method may give the reader an idea of the actual performance of GA-AFFG when minimizing all of the functions. Although the correct implementation of GA-AFFG is somewhat competitive (columns 4 and 5 in Table 1), all of the analysis reported in

[2] Basically, the authors claim that θ^i is an adaptive threshold that increases as the search process goes on, in such a way that the surrogate is less used for the final generations.

[3] The value of α was set to 0.9 as specified by the authors.

[4] It is well known that all of the functions from Table 2 are minimization tasks, but the authors approached them as maximization problems, see the comment below. We provide these plots in order to assess the validity of the proposed quantities when facing maximization tasks.