Use of guided genetic algorithms in optimization problems

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1 Introduction

Use of genetic algorithms (GA) in optimization problems is ubiquitous in mathematics [1, 2], engineering [3] and other fields such as economics [4, 5, 6]. In most optimization problems, the solution can be obtained by using numerical approximation techniques derived from the analytical expressions of the conditions on the critical points of a function or by directly using algorithms based on descent direction search techniques following different criteria. Several questions arise when considering these techniques, one of which may be the existence of possible local minima or the lack of knowledge of the geometry of the objective function and, therefore, of the behaviour of the algorithms used. It is in this framework that non-deterministic optimization methodologies appear and develop, in which the algorithms used do not offer the same results in each execution.

In exchange for this price to pay, these types of algorithms offer the possibility of obtaining different local minima when executed several times, thus facilitating the effective finding of the global minimum sought [7].

A large number of these techniques are available [8, 9, 10, 11], such as the stochastic approximation methods, stochastic gradient descent methods, simulated annealing, probability collectives, cross-entropy method, random search and swarm and evolutionary algorithms. Genetic algorithms(GA), initially popularized by Holland's work in the 1970s [12], fall into the latter category.

Their application is particularly suitable when there is not much data on any of the parts that determine the problem, such as the characteristics of the objective function or of the domain itself on which the function is defined, or on the way in which an "optimal direction" can be sought. It is generally agreed that genetic algorithms are more appropriate when the amount of information available on the problem is small. When sufficient information is available, more specialized methods tend to perform better. This research aims to partially fill this gap by considering ways to use the available information to improve GA competitiveness.

Genetic algorithms (GA) are initially inspired by the simulation of the evolution of species and their adaptation to the characteristics of the environment in which they live. A simple summary would be that we start from a randomly generated population of possible candidates for the solution of the problem on which some operators are defined: selection, crossover and mutation. Each

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individual has a score related to the goodness of the solution it represents. The selection operator is used to select the individuals to be crossed. The crossover produces new individuals that have the characteristics of their parents. The mutation operator is applied to some of these individuals, which randomly changes some characteristic. Successive applications of these operators cause the population to "evolve" towards better individuals.

A crucial point in the performance of GA applications to concrete problems lies in the coding scheme selected for the candidate solutions. The traditional approach is based on the use of bit arrays on which operators are simply defined. However, since the beginning of the research, the effects of different schemes have been studied, as integer coding [13, 14], schemes based on real numbers [14, 15, 16] and even object-based or complex schemes [17, 18, 19, 20]. Some studies review different schemes in a detailed way [21, 22, 23]

Despite its wide use, there are significant gaps in terms of theoretical support [7], the determination of the best parameters for solving a particular problem [24, 25, 26] or even the importance of the different operators [27].

The purpose of guided genetic algorithms is to apply heuristic techniques based on the knowledge of the problem and the behaviour of the solutions [28, 29]. These modifications to the traditional GA paradigm sometimes allow some of the difficulties inherent to these algorithms to be avoided, such as the problem of scalability with respect to the complexity of the problem to be dealt with or the optimization of adjustment functions with high computational cost.

In the present work, two applications of such guided genetic algorithms are presented for two domains using different coding schemes. On the one hand, a case of coding in real numbers is studied, focusing on the problem of diagonalization of symmetric or hermetic matrices [1, 2, 30, 31, 32, 33]. A second application studies the effect of the crossover and mutation procedures acting on a problem in which the optimization is performed in the space of permutations of a given order.

References

[1] Nandy, S., Chaudhury, P., Bhattacharyya, S. P. (2004). Diagonalization of a real-symmetric Hamiltonian by genetic algorithm: A recipe based on minimization of Rayleigh quotient. Journal of Chemical Sciences, 116, 285-291.

[2] Nandy, S., Sharma, R., Bhattacharyya, S. P. (2011). Solving symmetric eigenvalue problem via genetic algorithms: Serial versus parallel implementation. Applied Soft Computing, 11(5), 3946-3961.

[3] Taczala, M., Buczkowski, R. (2014). Eigenvalue analysis of stiffened plates resting on elastic foundation. In Maritime Technology and Engineering (pp. 513-520). CRC Press.

[4] Chang, T. J., Yang, S. C., Chang, K. J. (2009). Portfolio optimization problems in different risk measures using genetic algorithm. Expert Systems with applications, 36(7), 10529-10537.

[5] Chou, Y. H., Kuo, S. Y., Lo, Y. T. (2017). Portfolio optimization based on funds standardization and genetic algorithm. IEEE Access, 5, 21885-21900.

[6] Gkikas, D. C., Theodoridis, P. K., Beligiannis, G. N. (2022, May). Enhanced Marketing Decision Making for Consumer Behaviour Classification Using Binary Decision Trees and a Genetic Algorithm Wrapper. In Informatics (Vol. 9, No. 2, p. 45). MDPI.

[7] Peck, C. C., Dhawan, A. P. (1995). Genetic algorithms as global random search methods: An alternative perspective. Evolutionary Computation, 3(1), 39-80.

[8] Marti, K. (2015). Stochastic optimization methods. In Stochastic Optimization Methods: Applications in Engineering and Operations Research (pp. 1-35). Berlin, Heidelberg: Springer Berlin Heidelberg.

[9] Erten, H. I., Deveci, H. A., Artem, H. S. (2020). Stochastic optimization methods. In Designing engineering structures using stochastic optimization methods (pp. 10-23). CRC Press.

[10] Fouskakis, D., Draper, D. (2002). Stochastic optimization: a review. International Statistical Review, 70(3), 315-349.

[11] Gutjahr, W. J., Pichler, A. (2016). Stochastic multi-objective optimization: a survey on non-scalarizing methods. Annals of Operations Research, 236, 475-499.

[12] Holand, J. H. (1975). Adaptation in natural and artificial systems. Ann Arbor: The University of Michigan Press, 32.

[13] Damousis, I. G., Bakirtzis, A. G., Dokopoulos, P. S. (2004). A solution to the unit-commitment problem using integer-coded genetic algorithm. IEEE Transactions on Power systems, 19(2), 1165-1172.

[14] Shopova, E. G., Vaklieva-Bancheva, N. G. (2006). BASIC—A genetic algorithm for engineering problems solution. Computers and chemical engineering, 30(8), 1293-1309.

[15] Chuang, Y. C., Chen, C. T., Hwang, C. (2015). A real-coded genetic algorithm with a direction-based crossover operator. Information Sciences, 305, 320-348.

[16] Baskar, S., Subbaraj, P., Rao, M. V. C. (2003). Hybrid real coded genetic algorithm solution to economic dispatch problem. Computers and Electrical Engineering, 29(3), 407-419.

[17] Zhang, L., Wong, T. N. (2015). An object-coding genetic algorithm for integrated process planning and scheduling. European Journal of Operational Research, 244(2), 434-444.

[18] Wang, Y. M., Yin, H. L., Wang, J. (2009). Genetic algorithm with new encoding scheme for job shop scheduling. The International Journal of Advanced Manufacturing Technology, 44, 977-984.

[19] Li, X., Gao, C., Pu, R. (2014, August). A community clustering algorithm based on genetic algorithm with novel coding scheme. In 2014 10th International Conference on Natural Computation (ICNC) (pp. 486-491). IEEE.

[20] Snyers, D., Petillot, Y. (1995). Image processing optimization by genetic algorithm with a new coding scheme. Pattern Recognition Letters, 16(8), 843-848.

[21] Salomon, R. (1996, September). The influence of different coding schemes on the computational complexity of genetic algorithms in function optimization. In International Conference on Parallel Problem Solving from Nature (pp. 227-235). Berlin, Heidelberg: Springer Berlin Heidelberg.

[22] Kumar, A. (2013). Encoding schemes in genetic algorithm. International Journal of Advanced Research in IT and Engineering, 2(3), 1-7.

[23] Hancock, P. J. (1993). Coding strategies for genetic algorithms and neural nets.

[24] Goldberg, D. E., Deb, K. (1991). A comparative analysis of selection schemes used in genetic algorithms. In Foundations of genetic algorithms (Vol. 1, pp. 69-93). Elsevier.

[25] Yadav, S. L., Sohal, A. (2017). Comparative study of different selection techniques in genetic algorithm. International Journal of Engineering, Science and Mathematics, 6(3), 174-180.

[26] Rajakumar, B. R. (2013). Static and adaptive mutation techniques for genetic algorithm: a systematic comparative analysis. International Journal of Computational Science and Engineering, 8(2), 180-193.

[27] Fogel, D. B. (2006). Evolutionary computation: toward a new philosophy of machine intelligence. John Wiley and Sons.

[28] Navarro-González, FJ., Compañ, P., Satorre, R. Villacampa, Y., Numerical determination for solving the symmetric eigenvector problem using genetic algorithm *Applied Mathematical Modelling*, 40(7-8): 4935-4947, 2016.

[29] Villacampa, Y., Navarro-González, FJ., Compañ, P., Satorre, R. A guided genetic algorithm for diagonalization of symmetric and Hermitian matrices *Applied Soft Computing*, 75: 180–189, 2019.

[30] Schmitt, Lothar M., Theory of genetic algorithms *Theoretical Computer Science*, 259(1-2): 1-61, 2001.

[31] Zuo, W., Xu, T., Zhang, H., Xu, T., Fast structural optimization with frequency constraints by genetic algorithm using adaptive eigenvalue reanalysis methods *Structural and Multidisciplinary Optimization*, 43: 799-810, 2011.

[32] Sharma, R., Nandy, S., Bhattacharyya, SP., On Solving Energy-Dependent Partitioned Real Symmetric Matrix Eigenvalue Problem by a Parallel Genetic Algorithm *Journal of Theoretical and Computational Chemistry*, 7(06): 1103-1120, 2008.

[33] Nandy, S., Sharma, R., Bhattacharyya, SP., Solving symmetric eigenvalue problem via genetic algorithms: Serial versus parallel implementation *Applied Soft Computing*, 11(5): 3946-3961, 2011.