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An adaptive invasion-based model for distributed Differential Evolution

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ABSTRACT

A novel adaptive model for a recently devised distributed Differential Evolution algorithm is introduced. The distributed algorithm, following the stepping-stone model, is characterized by a migration model inspired by the phenomenon known as biological invasion. The adaptive model is endowed with three updating schemes to randomly set the mutation and the crossover parameters. These schemes are here tied to the migration and are guided by a performance measure between two consecutive migrations. The proposed adaptive model is tested on a set of classical benchmark functions over the different setting schemes. To evaluate its performance, the model is compared against the original non-adaptive version with a fixed parameter setting, and against a well-known distributed Differential Evolution algorithm equipped with the same schemes for the control parameter updating. The experimental study shows that the method results in high effectiveness in terms of solutions detected and convergence speed on most of the benchmark problems and for the majority of the setting schemes investigated. Finally, to further estimate its effectiveness, the proposed approach is also compared with several state-of-the-art Differential Evolution frameworks endowed with different randomized or self-adaptive parameter setting strategies. This comparison shows that our adaptive model allows obtaining the best performance in most of the tests studied.

1. Introduction

A way to improve the potential search moves of an Evolutionary Algorithm (EA) is via the employment of structured EAs in which the population is partitioned into several semi-isolated subpopulations (*demes*) connecting each other in accordance with a particular network topology [3]. The advantages of structured EAs are that they are able to explore a search space more evenly and can fight population stagnation thanks to a better capability of preserving an overall higher diversity [3]. This is because the separation of demes serves as a natural mode to maintain the diversity reducing the possibility of population stagnation [77,71], may guide the evolution in many directions simultaneously, and can allow speedup in computation and better solution quality in relation to a single EA evolution.

Among the structured EAs a key role is assumed by the distributed EAs (dEAs) [3] in which subpopulations explore in parallel the search space. Concerning the neighborhood topology, this distributed framework may be categorized as

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following either the *island model* (fully connected demes) or the *stepping-stone model* (interaction restricted to customized logically or physically connected demes) [46].

The exchange of individuals among neighboring subpopulations is controlled by the migration policy [12]. The number of individuals that are sent to (received from) other demes is determined by the *migration rate*, while the *selection function* individuates the individuals to exchange and the *replacement function* defines how to include the immigrants into the target subpopulation. Besides, the *migration interval* establishes the exchange frequency among neighboring subpopulations.

Several island and stepping-stone EA models differing in the selection function, the replacement function, the migration rate and intervals, and the topology have been proposed in literature [13,49,64,2]. Usually, this kind of dEAs exchanges individuals, selected by some specific characteristics, between the islands with a ratio equal to one: each immigrated individual substitutes an individual in the receiving subpopulation. Besides, such a substitution mostly occurs by either a swap or a copy-and-replacement.

In the last years much research activity has been dedicated to the development of distributed Differential Evolution (dDE) approaches [21,36,28,20,16,38]. The choice of DE within the distributed framework is due to the fact that this evolutionary strategy requires few control parameters, shows a solid performance for complex continuous optimization problems in terms of final accuracy, convergence speed, and robustness, and outperforms many of the already existing stochastic and direct search global optimization techniques [57,48,19], also when multimodal problems are faced [5]. From an algorithmic viewpoint, the reason for the success of DE is due to an implicit self-adaptation contained within the particular evolutionary search implemented by it [29]. Since, for each candidate solution, the search operator depends on other solutions belonging to the population, the ability to detect new promising offspring depends on the current distribution of solutions within the decision space, on the ability to explore this space and to exploit the most promising search directions. These capabilities are affected by the setting of the control parameters.

Starting from the previous considerations, we have recently proposed an Invasion-based migration Model for dDE (IM-dDE) [22,23], characterized by an innovative migration strategy inspired by the biological phenomenon known as *biological invasion* [63]. With the aim to exploit the features of biological invasions, IM-dDE distinguishes itself from the parallel evolutionary migration strategies by both the number of individuals spread from a deme to another, and by the way such individuals are used to update the receiving population. In particular, we have devised a stepping-stone DE based on a multistage process for the invasion involving a group of migrating individuals from all the neighboring demes, and on their competition with native individuals to generate a new local subpopulation.

IM-dDE, as the classical DE algorithm, uses empirically chosen values for its parameters that are kept fixed through the whole optimization process. Although this control mechanism seems, at first glance, unsophisticated and efficient, it hides a drawback: the DE scheme has for each generation a limited amount of exploratory moves and, if these moves are not sufficient to generate new promising solutions, the search ability can be heavily damaged [47]. Hence, despite its positive aspects, it is clear that to improve the DE performance appropriate strategies are necessary to deal with the critical problem of the control parameter setting [42].

The randomization of this setting seems to represent an efficient way to allow an enlargement in the number of the search moves and thus to provide a better chance to detect solutions with better performance [18,7]. Many strategies, ranging from more or less sophisticated randomization to self-adaptive logic or dynamic schemes, have been devised to find an adequate response to the *exploration/exploitation dilemma* in DE [28,19,7,73,80,58,76,74]. All these strategies, aiming to reduce the probability for an unsuitable choice of the control parameters, may lead to a premature convergence or to an undesired stagnation condition [18,40,27].

Within this paper we introduce and investigate a novel adaptive model endowed with three updating schemes for randomly setting DE control parameters in order to improve the IM-dDE performance. Hereinafter, the resulting adaptive algorithm is referred to as Adaptive Invasion-based migration Model for dDE (AIM-dDE).

The adaptive procedure occurs at each migration time and is based on two steps. Firstly a local performance measure related to the average fitness improvement for each subpopulation is computed. Secondly, a specific updating scheme based on these measures takes place to randomly update the control parameter values of some subpopulations.

Based on the fitness feedback, the adaptive updating process aims to favor an improvement in the exploration in the parameter space in those subpopulations that improve their performance less than the others. The hope is that eventually such subpopulations will find good parameter values, thus enhancing their performance. In general all the updating schemes are employed for a dynamic setting of both the mutation and the crossover parameters, where the subpopulation size is assumed to be tuned in advance and kept fixed throughout the evolution process.

To assess its effectiveness, AIM-dDE algorithm is compared with the original model with a fixed parameter setting (IM-dDE), with a well-known dDE, namely DDE [21], and with a variant of DDE provided with the same updating schemes, hereinafter denoted as A-DDE. For completeness two non-adaptive randomized schemes are also considered. Moreover, a comparison with different adaptive variants of both dDEs and sequential DEs, recently proposed in literature, is carried out.

The paper is organized as follows: Section 2 illustrates the DE technique while the state of the art on control parameter setting strategies is reported in Section 3; Section 4 presents AIM-dDE with its parameter setting schemes. In Section 5 the experimental findings, in terms of solutions detected and convergence speed, of the adaptive strategies are shown and discussed, a statistical analysis is presented, and the behavior of the model with the different schemes is investigated. Finally, the last section contains conclusion remarks and future works.