Synergy between convergence and divergence – review of concepts and methods

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Abstract. Modern Industry 4.0 technologies face a challenge in dealing with billions of connected devices, petabyte-scale of generated data, and exponentially growing internet traffic. Artificial Intelligence and Evolutionary algorithms can resolve variety of large optimisation problems. Many methods employed in search for solutions often fall in stagnation or in unacceptable results, which reminds for classical dilemma exploration versus exploitations closely related with convergence and diversity of the explored solutions. This article reviews convergence and divergence centred algorithms and discuses synergy between convergence and divergence in adaptive heuristics.

Keywords: Convergence, divergence, synergy, adaptive heuristic algorithms, Tabu search, Particle Swarm Optimisation, Genetic algorithms, Differential Evolution, Scatter search, Novelty search, Surprise search, Free Search.

1 Introduction

Exponentially growing number of connected devices, generated data and internet traffic demands fast and efficient methods which can provide optimal solutions in technology and science. The concept for natural selection and generation of new species applied to computational optimisation could help to improve optimisation process for large scale task. In this context Evolutionary computation (EC) as a branch of computational intelligence, included into the broad framework of bio-inspired heuristics needs more research efforts.

According to [11], in contrast to the natural evolution artificial evolution in Evolutionary Computation suffers an endemic lack of diversity during evolutionary optimisation processes and all candidate solutions frequently homologize. This situation is usually described as stagnation or premature convergence to a local suboptimum.

To cope with stagnations are proposed many approaches. [2][3][7][9][13] This article discuses synergy between convergence and divergence in adaptive heuristic algorithms, aims to highlight and compare strengths and limitations of existing algorithms.

2 Methodologies review

This section reviews classical and novel algorithms with specific original concepts such as Tabu search [5], Particle Swarm Optimisation [2], Genetic algorithms [3][7], Differential Evolution [13], Scatter search [6], Novelty search [8], Surprise search [4], Free Search [9]. Most of these techniques are effective on of limited types of landscapes and implemented concepts can lead to improvement of further methods. Some of them are dominated by convergence process, other intentionally try to diverge over the search space to generate appropriate diversity or to achieve other objectives.

2.1 Convergence centred methods

This section reviews several methods base on modification strategy, which aims to converge to the optimal solution and using specific techniques and approaches to prevent and avoid premature convergence to suboptimal locations.

2.1.1 Tabu search

The Tabu Search idea is - “Tabu search is a meta-strategy for guiding known heuristics to overcome local optimality” [5]. Tabu Search is based on the temporary prohibition of moves in order to avoid cycles in the search trajectory [1]. Some open problems of Tabu Search are: - the determination of an appropriate "prohibition" for a given task, the adoption of minimal computational complexity algorithms for using memory, the robustness of the technique for a wide range of different problems [1]. Using the concept of Tabu Search, a local search can be guided to go beyond local optima through meta-heuristic methods that use the information obtained in the previous part of the run. In the Reactive Tabu Search (RTS) algorithm a simple feedback scheme influences the value of the prohibition parameter in the Tabu Search, so that a balance of exploration versus exploitation is obtained that is appropriate for the local characteristics of the task [1]. The concept of Tabu Search aims to facilitated convergence but limits divergence across the whole space.

2.1.2 Particle Swarm Optimisation

Particle Swarm Optimisation (PSO) is motivated by social behaviour of organisms such as bird flocking and fish schooling. PSO is a method for optimisation of continuous non-linear functions [2]. PSO algorithm is not only a tool for optimisation, but also a tool for representing socio-cognition of human and artificial agents, based on principles of social psychology. Some scientists suggest that knowledge, which is optimised by social interaction and thinking is not only private but also interpersonal.

In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and according to the experience of a neighbouring particle, making use of the best position encountered by itself and its neighbour. PSO combines local search methods with global search methods, attempting to balance exploration and exploitation [2].

Aim of the adjustment based on best positions is to converge to the optimum. This concept to certain extent limits divergence over the whole search space.

2.1.3. Genetic Algorithms

Genetic algorithms (GA) are a family of computational models inspired by Darwin's theory about evolution [7][14]. An algorithm is started with a set of solutions (represented by chromosomes) called “population”. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions, which are selected to form new solutions (offspring), are chosen according to their fitness - the more suitable they are the more chances they have, to reproduce. This is repeated until some condition (for example expiration of the period for search or improvement of the best solution) is satisfied. The GA has wide range of modifications and variations according to representation of the variables, recombination strategies, modification strategies and replacement strategies. An original idea explored in real-value The Genetic Algorithm is implemented and coding BLX-α modification [3]. The real coded BLX-α GA also selects two parents from the current population, makes a crossover between them and produces an offspring (new solution). The offspring can mutate with small probability. Then the GA incorporates the offspring in the new generation if it is better than an individual from current generation. Aim of the crossover is to converge to the optimal solution, while the aim of mutation is to diverge over the search space. Balance, between these processes, relays on random generation. For large scale tasks this leads to the need for large number of iterations, computational resources, and time.

2.1.4. Differential Evolution

Differential Evolution (DE) [13] is based on the idea for generating trial parameter vectors. It is an optimiser for multivariate functions. Starting from an initial random population of points (interpreted as vectors) the procedure iteratively updates the population using two basic operations: mutation and recombination. DE is applicable to functions that are non-differentiable, non-linear, or otherwise resistant to traditional approximation techniques. A similar technique used by neural researchers to deduce network functions from data samples, simulated annealing, could also model non-linear/non-differentiable functions, but DE is faster and requires fewer restarts [13].

Aim of recombination in DE is to converge to the optimal solution, and the aim of mutation is to diverge over the search space. Balance, between these processes can be controlled by different modification strategies. [10].

2.2 Divergence centred methods

This section focuses on methods which utilises divergence and applies specific techniques for identification of appropriate solutions and termination of the process.

2.2.1. Scatter Search

According to the literature "The Scatter Search process, building on the principles that underlie the surrogate constraint design, is organized to capture information not constrained separately in the original vectors, and to take advantage of auxiliary heuristic methods both for' selecting the elements to be combined and for generating new vectors." [6]. The original form of scatter search [6] can be presented in the following 3 steps: (1) Generate a starting set of solution vectors by heuristic processes designed for the problem; (2) Create new points consisting of linear combinations of subsets of the current reference solutions. The linear combinations are chosen to produce points both inside and outside the convex regions spanned by the reference solutions, modified by generalized rounding processes to yield integer values for integer-constrained vector components. (3) Extract a collection of the best solutions generated in Step 2 to be used as starting points for a new application of the heuristic processes of Step 1. Repeat these steps until reaching a specified iteration limit. Three features of Scatter Search deserve attention: - First the linear combinations are structured according to the goal of generating weighted centres of selected sub-regions, allowing for no convex combinations that project these centres into regions external to the original reference solutions. Second, the strategies for selecting particular subsets of solutions to combine in Step 2 are designed to make use of clustering, which allows different types of strategic variation by generating new solutions 'within clusters' and 'across clusters'. Third, the method is organized to use supporting heuristics that can start from infeasible solutions, and which removes the restriction that solutions selected as starting points for re-applying the heuristic processes must be feasible. [6].

The concept of Scatter Search can be classified as an example which aims to utilise predominantly divergence.

2.2.2. Novelty Search

Novelty Search algorithm [8] is based on the concept for open-ended evolutionary system, which continually produces novel forms [12]. This is different from other evolutionary algorithms, which aim to achieve optimal solution. The Novelty Search utilises the divergence over the search space, which relays on the hope that the groped optimal value can be achieved accidentally. It is acknowledged that: “it is likely more efficient to take the most promising results from novelty search and further optimize them based on an objective function. This idea exploits the strengths of both approaches: Novelty Search effectively finds approximate solutions, while objective optimization is good for tuning approximate solutions. Alternatively, novelty search could be applied when a traditional evolutionary algorithm converges, to replenish diversity in the population.” [8]

Proposed modification strategy uses distance between the solutions and factors based on previous experiments to generate divergence from current locations.

2.2.3. Surprise Search

Surprise Search as stated in [4] can also be classified as a divergence centred search algorithm which has demonstrated acceptable performance on robot morphology evolution, maze navigation, and other two-dimensional tasks. According to the literature [4] it modifies Novelty Search. Divergence is based on a definition of surprise as “deviation from the expected.”

Surprise Search modification strategy inherits modification strategy concept based on distance. The distance is generated on past difference and expectations for further behaviour. This, two steps, approach favours individuals that diverge from predicted future trends. With certain probability the predictions could be infeasible or unreachable by conventional search when applied to real tasks such as points outside a maze that should be traversed.

Proposed in Surprise Search divergence strategy brings improvements appropriate for certain applications. [4]

3 Synergy between convergence and divergence

This section illustrates the Free Search concept published earlier. Free Search is adaptive heuristic method [9] for real coded optimisation. This algorithm harmonises divergence and convergence using highly unlimited modification strategy and natural relations between stochastically generated values [9].

Optimisation process starts with exploration over the search space implemented as individual journeys within their neighbour space [9]. In the beginning algorithm has no knowledge about the search space and exploration is highly random. This is achieved by multiplication of several stochastic variables. The first exploration generates knowledge stored in a form of qualitative indicators related with evaluated locations. These indicators facilitate individuals' sensibility for orientation within the search space for further search. [9]

On initial stage locations quality and individuals' sensibility are uniformly distributed among low, medium, and high levels. Individuals with low level of sensibility can select for start position any marked location. The individuals with high sensibility can select for start position marked locations with high quality and will ignore locations with low quality. When marked locations quality highly differs and stochastically generated sensibility produces accidentally high values only, then the individuals will search around the area of the highest quality solutions. Such situations appear naturally. In this manner process converges to high quality locations. [9]

Other situation which naturally appears is when marked locations qualities are very similar and randomly generated sensibility is low. In this case individuals can select low quality marked locations with high probability, which indirectly will decrease the probability for selection of high-quality marked locations. Individuals with low sensibility can select to explore around locations marked with low quality.

As far as locations quality is independent on their position within the search space, similar quality locations could be remotely distributed. This facilitates divergence across the entire search space. Sensibility varies across all the individuals and during the optimisation process. In this manner convergence and divergence are harmonised in the search of optimal solution. It helps to minimise generated new solutions according to the achieved quality.

Modification strategy is independent on the distance, which prevent generation of many location if applied to large scale tasks. [9]

4 Discussion

Modern Industry 4.0 technologies face several challenges such as: - maximising connected devices; optimising use of infrastructure; maximising processed data; minimising use of resources; maximising internet traffic; minimising traffic delays; maximising number of users and minimising energy use, and waste. All of these are optimisation problems, at large and growing scale.

In this context reasonable hope relies on Artificial & Computational Intelligence and Evolutionary & Heuristic algorithms, which can resolve variety of large optimisation problems.

Often methods employed in large scale search converge prematurely and fall in stagnation. A promising approach, which can help to escape from or prevent premature convergence is synergy between convergence & divergence.

5 Conclusion

This article reviews several classical and novel convergence centred and divergence centred algorithms. Discussion on synergy between convergence and divergence highlights the role of evolutionary and heuristic optimisation methods in optimisation, of demanded by Industry 4.0 large scale tasks. Presented review of classical and novel algorithms and concepts suggests a good potential for synergy between convergence & divergence. More further research efforts in this area should be done.

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