Firefly Algorithm for Finding Optimal Shapes of Electromagnetic Devices

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Many real world optimization problems have to be treated as multi-objective optimization problems. Relying on scalar optimization methods, a suitable objective function taking all objectives into account has to be defined. Besides that, in the feasible region of the trial variables a remarkable number of local solutions could be expected, one of them resulting in the best value of the chosen objective function. Therefore, a scalar optimization strategy should be able to end up in the best of all possible solutions (in the given search space) and additionally detect as many local solutions as possible. The Firefly Algorithm (FFA), one of many metaheuristic optimizatzion methods, mimics the natural behaviour of fireflies, which use a kind of flashing light to communicate with other members of their species. The information conveyed can be either the message about the quality of food supply, but it can also be a notice about possible threats. A Clustered Firefly Algorithm will be applied to detect as many local solutions as possible on its way to the best solution in the given search space and its performance will be compared to a Niching Higher Order Evolution Strategy (NES).

***Index Terms*—Optimization, Particle swarm optimization, Evolutionary computation, Pareto Optimization**

I. Introduction

THE application of stochastic optimization algorithms for the optimization of technical design problems has become a well established and approved approach over the last decades. Methods using simplified sequences of very complex natural processes are among the most successful ones of this class. Unfortunately, their major advantages like numerical stability and high convergenge rate are still foiled by the high number of evaluations of the objective function. Despite the enormous increase in CPU power, this inherent feature of stochastic methods may make them unfeasible in case of problems with computationally "'expensive"' forward problems. Therefore, a major goal of any improvement of stochastic methods is to extract as much information as possible from as few function calls as reasonable.

Much emphasis has already been put on swarm-based meta-heuristics [1]. Inherent to all these methods is some way of transferring information from individual to individual. Fireflies, which are also forming swarms, do this by using a kind of flashlight to attract other individuals [2]. The luminosity of a single firefly decreases radially in a certain way. Since the total light intensity of a crowd of fireflies depends on the number of insects and their individual luminosity, this 'integral' feature can advantageoulsy be used to form fractions of swarms, which can be expected in the vicinity of locally optimal solutions.

This 'multi modal' performance of the clustered Firefly Algorithm is compared to a Niching Higher Order Evolution Strategies (NES)[3],[4], which relies on a modified recombination operator to identify niches of good solutions. Both strategies are applied to multi modal test functions for comparison of the number of function calls, global bevaviour and number of detected local solutions and to a real world 2D shape optimization problem, a magnetic shielding problem.

II. The Magnetic Shunt/Shielding Problem

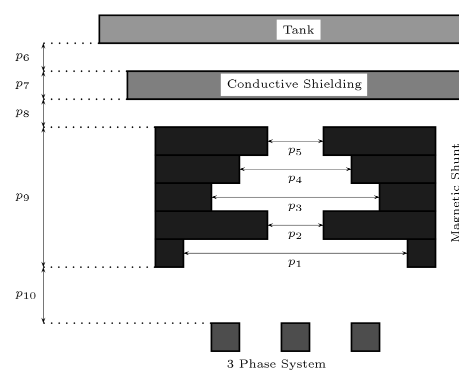


Fig. 1. Shunt Problem with Trial Variables p_1 to p_{10}

Figure 1 shows the magnetic shunt/shield problem [5]. The magnetic field, produced by a three phase system, leads to eddy currents. Magnetic shunts and a layer of copper are arranged and optimized in shape in such a way, that the total power losses are minimized while keeping the material costs of the shields and the copper layer as small as possoible.

III. Optimization Strategy: Firefly Algorithm

The swarm behaviour of fireflies is abstracted for use in an optimization algorithm. The following simplified rules are taken into account [2].

- All fireflies are unisex. They therefore will be attracted to any other firefly equally.
- Attractiveness of a firefly is proportional to its brightness. A less bright firefly will move towards the brighter one.

Brightness, and therefore attractiveness, decreases with the distance between the fireflies. The brightest fireflies will move randomly.
- The brightness of a firefly is determined by the landscape of the objective function.

In the beginning a starting population will be constructed randomly. Then in each time step, the positions of all fireflies will be updated according to the attractiveness of all other fireflies in the population. This happens according to the following rule (1) [6].

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha^t \epsilon_i^t. \qquad (1)$$

The parameter t is the current iteration step, x_i^{t+1} and x_i^t are the new and the old position of firefly i, respectively; x_j^t is the position of the firefly j to be compared with; α, β_0 and γ are strategy parameters and ϵ, the random move is drawn from a proper distribution. $r_{i,j}$ is the Euclidian distance between the two individuals compared to each other. Other metrics can be used as well in this context.

A. Strategy Parameters of the Firefly Algorithm

The parameters in (1) are discussed in some detail here. Every movement of a firefly should include a random step ϵ_i^t to explore the parameter space. Different probability distributions can be used to construct ϵ_i^t. The size of this random step is controlled by a parameter α. This parameter is responsible for how much the space of the trial variables is explored by individual fireflies at a given stage t of the optimization process. Usually this factor α is updated in every iteration step by $\alpha^{t+1} = \alpha^t \delta$, where the factor δ is chosen between 0.9 and 0.99. It can be seen, that the size of the random steps is getting smaller and smaller over the course of the algorithm.

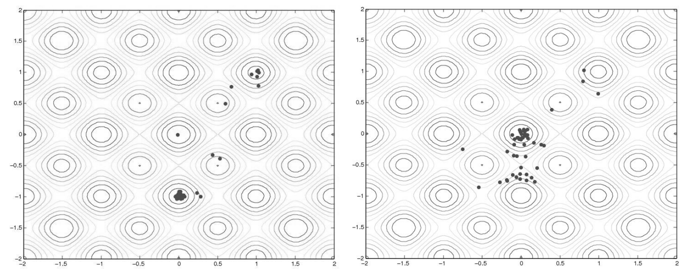
The parameter β_0 scales the attractiveness of fireflies, while the parameter γ can be interpreted as an absorption coefficient, defining how much light will be absorbed by the 'parameter space'.

In a single iteration step each individual has to be compared with all others in the population, probably followed by an update step as shown in (1). This computitional effort can be reduced remarkable if the population is clustered into proper fractions with an integrated impact on the remaining individuals of the population.

IV. Results

A. Rastrigin Function

A FFA with α = 0.2, β_0 = 1, γ = 1 and δ = 0.97 is used to find optimal solutions of the Rastrigin function. An interesting feature of the algortihm is summarized here. In Fig. 2 (a) an iteration step is shown, where most flies have already gathered around local solutions. In this stage of the optimization process, the strategy can report about these local solutions, e.g. by applying a cluster algorithm [4]. But it can be seen too, that one individual by chance is close to the global solution at (0,0). This firefly stays there (it cannot be attracted by any other fly), sends the 'brightest light' to the others and starts to attract more and more fireflies of the population as can be seen in Fig. 2 (b).



(a) One fly close to the locally best solution (b) Flies crowd together around the locally best solution

Fig. 2. Global Behaviour of the Firefly Algorithm

This leads to a kind of 'global performance' and all fireflies crowd togehther in this locally best solution.

B. The Magnetic Shunt/Shielding Problem

A FFA with the same startegy parameters as given above is used to solve the magnetic shunt/shielding problem. The electromagnetic field problem is solved using the 2D Finite Element code ELEFANT2D [8]. For a first result only the magnet shunts were taken into account. The trial variables (Fig. 1) were adjusted in order to reduce the eddy currents while keeping the volume of the shunts small. The objective function was composed from the two objectives using a weighted sum of fuzzy membership functions [7].

The best result was able to decrease the volume by 53% and the eddy current losses by 40% compared with a massive shunt of the same dimensions.

V. Conclusion

The clustered FFA is able to detect a number of locally optimal solutions while arriving at the global solution (in a given feasible region) with a rather high probabilty. Clustering the firefly population constantly and "'summing"' up the impact of a cluster of fireflies on individuals outside the cluster can reduce the computational effort remarkably, as will be shown in the full paper.

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