Evolutionary Hybrid Genetic-Firefly Algorithm for Global Optimization

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Abstract

The paper presents the Evolutionary Hybrid Genetic-Firefly algorithm for the optimization of complex problems and to search global solution more precisely. In this algorithm the idealized rules of the firefly algorithm i.e. swarm behaviour is combined together with the evolutionary strategy, i.e. the survival of the fitness strategy of the genetic algorithm to evolve a Hybrid algorithm. In the hybrid evolution the genetic algorithm searches the solution space for global minimum and the Firefly algorithm improves the precision of the potential candidate solution. The proposed strategy was implemented on various benchmarking test functions to evaluate the general performances of the individual algorithms and Hybrid Genetic-Firefly algorithm in terms of rate of convergence, precision and robustness to find the global best solution. The simulation results clearly illustrate that the proposed strategy is very effective in finding the global solution precisely.

Keywords: Global Optimization, Genetic Algorithm, Firefly Algorithm, Hybrid GA-FA Algorithm, Validation.

1. Introduction

In traditional optimization approach the sequential optimization is used where one parameter is optimized at a time while keeping the other parameters fixed and repeating the optimization for the remaining other parameters sequentially in one complete iteration. Several iterations are required to determine the optimal parameters for an objective function to be optimized. When the number of parameters to be optimize is large the classical techniques requires large number of iterations and computation time. Thus, for problems with large search space and with many local optima, evolutionary algorithms have become a popular choice [6]. The main motivation for using evolutionary algorithms, to solve an optimization problems is because the evolutionary algorithms deal simultaneously with a set of possible solutions called population which allows us to find several members of the Pareto optimal set in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of the traditional mathematical programming techniques. Additionally, evolutionary algorithms are less susceptible to the shape or continuity of the Pareto front, whereas these two issues are known problems with mathematical programming techniques. The population based collective learning process, self-adaptation, and robustness are some of the key features of evolutionary algorithms when compared to other global optimization techniques. Also evolutionary algorithms offers practical advantages such as multi-fold, including the simplicity of the approach, its robust response to changing circumstances, its flexibility and many other aspects [14], [15]. The present context emphasizes on the implementation aspects of the evolutionary algorithms such as genetic algorithm, Firefly algorithm and the hybrid algorithm that combines the potential features of Genetic algorithm and Firefly algorithm to evolve as a new Hybrid Genetic-Firefly algorithm which explores the search space for optimal solution more precisely.

2. Evolutionary Genetic Algorithm

Genetic algorithms (GAs) are stochastic, population-based search and optimization algorithms inspired by the process of natural selection and genetics. They are based on the genetic processes of biological organisms. Over many generations, natural populations evolve according to the principles of natural selection and "survival of the fittest". By mimicking this process, genetic algorithms are able to "evolve" solutions to real world problems, if they have been suitably encoded. Genetic algorithm (GA) is an optimization method based on the mechanics of natural selection. In nature, weak and unfit species within their environment are faced with extinction by natural selection.
The strong ones have greater opportunity to pass their genes to future generations. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection [1]-[3], [15].

For many of the problems in industrial engineering, it is nearly impossible to represent their solutions with binary encoding. Real number encoding is best used for optimizing real world problems [2]. In real-coded genetic algorithm (RCGA) a solution is directly represented as a vector of real parameter decision variables, representing the solutions very close to the natural formulation of the problem. The use of floating-point numbers in the GA representation has a number of advantages over binary encoding. The efficiency of the GA gets increased as there is no need to encode/decode the solution variables into the binary type.

2.1. Chromosome structure

In GA terminology the potential solution to a problem can be represented as a set of decision variables to be optimized. These individual parameters known as genes are joined together to form a string of values called as chromosome. Each gene in the string controls one or more features of the chromosome [2], [15].

2.2. Selection

During the reproduction phase of the Genetic algorithm, individuals are selected from the population and recombined to produce new offspring’s which will comprise the next generation. The selection process directs the search towards the promising regions of feasible solution in the search space. Among the various selection schemes, tournament selection is promising one due to its efficiency and implementation. In tournament selection, \( n \) individuals are selected randomly from the larger population, and the selected individuals compete against each other. The individual with the highest fitness wins and will be included as one of the next generation population [2], [15].

2.2. Crossover

Crossover operator is an important operator of GA as it increases the diversity of the population and evolves new solution which may potentially optimize the problem. In crossover two chromosomes called parents are selected among the population with preference towards the fitness value and forms new chromosomes called offspring [1], [2], [15]. Among the various crossover methods, *Arithmetic crossover* is adopted. For the crossover operation one best chromosome based on the fitness value and a random chromosome from the population is selected as parents and offspring are generated according to:

\[
\begin{align*}
\text{Child}_1 &= r \times \text{Parent}_1 + (1-r) \times \text{Parent}_2 \\
\text{Child}_2 &= r \times \text{Parent}_2 + (1-r) \times \text{Parent}_1
\end{align*}
\]

2.3. Mutation

Mutation is the secondary operator of GAs to explore a solution space. The mutation operator introduces random change into the characteristic of chromosome thereby reintroduces genetic diversity into the population and thus overcomes local traps by slightly perturbing current solutions [1], [2], [15]. Among the various mutation methods *Uniform mutation* is adopted.

2.4. Elitism

Elitism is a technique to preserve and use previously found best solutions in subsequent generations of EA. In an elitist EA, the population’s best solutions cannot degrade with generation.

3. Firefly Algorithm

The Firefly Algorithm (FA) is a metaheuristic, nature-inspired, optimization algorithm which is based on the social flashing behaviour of fireflies, or lighting bugs. It was developed by Dr. Xin She Yang at Cambridge University in 2007, and it is based on the swarm behaviour such as fish, insects, or bird schooling in nature [4]-[5], [14]. Its main advantage is the fact that it uses mainly real random numbers, and it is based on the global communication among the swarming particles i.e., the fireflies, and as a result, it emerges as an effective for multi-objective optimization. The flashing light is produced by a process of bioluminescence, and serves as the functioning signals to attract (communication) and to attract potential prey. The light intensity at a particular distance from the light source follows the inverse square law. That is as the distance increases the light intensity decreases. Furthermore, the air absorbs light which becomes weaker and weaker as there is an increase of the distance. There are two combined factors that make most fireflies visible only to a limited distance that is usually good enough for fireflies to communicate each other. The flashing light can be formulated in such a way that it is associated with the objective function to be optimized. The
main steps of the FA start from initializing a swarm of fireflies, each of which is determined the flashing light intensity. During the comparison of light intensity, the firefly with lower light intensity will move toward the higher one. The moving distance depends on the attractiveness. After moving, the new firefly is evaluated and updated for the light intensity. During pairwise comparison loop, the best-so-far solution is iteratively updated. The pairwise comparison process is repeated until termination criteria are satisfied. Finally, the best-so-far solution is visualized based on the ranking.

3.1. Firefly initialization

Each encoded operation is randomly selected and sequenced until all operations are drawn in order to create a firefly, which represents a candidate solution [4]-[5]. This random selection is repeated to generate a swarm of fireflies with the required size.

3.2. Firefly evaluation

The next stage is to measure the flashing light intensity of the firefly, which depends on the problem considered.

3.3. Attractiveness

As light intensity decreases with the distance from its source and light is also absorbed in the media, so we should allow the attractiveness to vary with degree of absorption. The light intensity \( I(r) \) varies with distance \( r \) monotonically and exponentially. That is:

\[
I = I_0 e^{-\gamma r}
\]  
(2)

Where \( I_0 \) the original light intensity and \( \gamma \) is the light absorption coefficient. As firefly attractiveness is proportional to the light intensity seen by adjacent fireflies, thus the attractiveness \( \beta \) of a firefly can be defined by

\[
\beta = \beta_0 e^{-\gamma r^m} \quad m > 1
\]  
(3)

Where, \( r \) is the distance between any two fireflies, \( \beta_0 \) is the initial attractiveness at \( r = 0 \) and \( \gamma \) the absorption coefficient which controls the decrease of the light intensity.

3.4. Distance

The distance between any two fireflies \( i \) and \( j \), at positions \( x_i \) and \( x_j \), respectively, can be defined as a Cartesian or Euclidean distance as follows

\[
r_{ij} = \left| x_i - x_j \right| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}
\]  
(4)

3.5. Movement

The movement of a firefly \( i \) which is attracted by a more attractive (i.e., brighter) firefly \( j \) is given by the following equation:

\[
x_{i+1} = x_i + \beta_0 e^{-\gamma r^m} (x_j - x_i) + \alpha (rand - 0.5)
\]  
(5)

Where the second term is due to the attraction while the third term is the randomization with \( \alpha \) being the randomization parameter. \( rand \) is a random number generator uniformly distributed in the range of \([0, 1]\).

3.6. Adaptive Step Length

In standard Firefly algorithm, firefly movement step length is a fixed value. So all the fireflies move with a fixed length in all iterations. If step size is very high then the precision gets low although the candidate solution reaches the vicinity of optimum point quickly. It moves around the optimum for the remaining iterations. If the step size is very small then it takes many iterations to reach the optimum point. So the rate of convergence decreases. For small number of iterations it may not reach optimum position. Hence the step size of each firefly is the main determining factor for both the speed of convergence. In proposed algorithm, step length \( \alpha \) depends on iterations and it decreases with increase of iterations and thus maintaining the precession of the solution.

4. Hybridization

The main motivation for the hybridization of different algorithmic concepts has been to obtain better performing systems that combine advantages of the individual algorithm strategies [9]-[11], i.e., Genetic algorithm (GA) and Firefly algorithm (FA). The hybridization of the algorithm is carried out in two phases; first the diversification of the algorithm to search the optimal solution is achieved by using the genetic operators such as selection, crossover and mutation operations. Secondly the precession of the algorithm to search the optimal solution is intensified by using the swarm behaviour of the Firefly algorithm. Firefly algorithm has some disadvantage such as trapping into several local optimums. Firefly algorithm do local search as well and sometimes can’t get rid of them as the firefly parameters are set fixed and they do not change by time.
Initialization

Define the objective function \( F(x) \):
Generate initial population \( x_i; i=1, 2, ..., n \).
Light intensity/Fitness value of population \( i \) is determined by objective function \( F(x_i) \).
Define the firefly algorithm parameters \( \alpha, \beta, \gamma \).
Define Genetic algorithm parameters \( p_c, p_m \).

While \( itr \leq \text{Max gen} \)
Apply evolutionary Genetic algorithm operators
Selection: Select the individuals, called parents that contribute to the population at the next generation. In the proposed GA tournament selection is used.
Crossover: Generate an offspring population Child,
If \( p_c > \text{rand} \),
Choose one best solutions \( x \) from the population based on the light intensity/fitness value and random solution \( y \) from the population for crossover operation. Using a crossover operator, generate offspring and add them back into the population.
Child\(_1\) = \( r \) parent\(_1\) + \((1 - r)\) parent\(_2\);
Child\(_2\) = \( r \) parent\(_2\) + \((1 - r)\) parent\(_1\);
End if
Mutation: Mutation alters an individual, parent, to produce a single new individual, child.
If \( p_m > \text{rand} \),
Mutate the selected solution with a predefined mutation rate.
End if
For \( i=1:n \)
For \( j=1:n \)
Light intensity \( l(x) \) is determined by objective function \( F(x_i) \).
If \( l_i < l_j \),
Then move firefly \( i \) towards firefly \( j \) (move towards brighter one)
End if
Attractiveness varies with distance \( r \) via \( \exp[-\gamma \ r] \). Evaluate new solutions and update light intensity.
End for j loop
End for i loop

Fitness assignment: Evaluate new solutions and update light intensity.
Stopping criterion: If the maximum number of generations has reached then terminate the search otherwise go to next iteration.
End while

Algorithm 1: Evolutionary Hybrid Genetic-Firefly Algorithm

Genetic algorithm on the other hand also suffers from premature convergence disadvantage and gets trapped at the local minimum. These disadvantages of genetic and firefly algorithm can overcome by generating new solutions in the population by adopting the genetic algorithm features “survival of fittest” and the “swarm behaviour” of firefly algorithm which may find better solutions and make a balance between global and local search. Also it can get rid of trapping in to several local optimums.

One prominent feasible feature that engenders hybridization is that, both genetic algorithm and firefly algorithm handles real numbers and hence there is no need to encode or decode the decision variables for the evolutionary algorithm operators. Genetic algorithm searches the solution space for global minimum and the Firefly algorithm improves the precession of the potential candidate solution.

5. Validation of the algorithm

Validation of the algorithm is essential to investigate the diverse properties of the algorithm so as to make sure whether or not the proposed algorithm can solve the specified type of optimization problem efficiently. The proposed algorithm is tested against standard benchmarking test functions so as to compare its general performances such as rate of convergence, precession and robustness [2]-[5].

5.1. Overview of benchmarking test functions:

There are many test functions available for the validation of an algorithm. Some of the major benchmarking functions used for investigating the performance [2]-[5] of Genetic algorithm (GA), Firefly algorithm (FA) and Hybrid Genetic-Firefly algorithm (GA-FA) were as follows:

5.1.1. Test function: De Jong’s function

The first function of De Jong’s called sphere function is one of the simplest test benchmark. The function is continuous, convex and uni-modal. It has the following general definition:

\[
f(x) = \sum_{i=1}^{n} x_i^2 \quad (6)
\]

Test area is usually restricted to hyper cube subjected to -5.12 \( \leq x_i \leq 5.12, \ i = 1, \ldots, n \). Global minimum \( f(x) = 0 \) is obtainable for \( x_i = 0, \ i = 1, 2, \ldots, n \).
5.1.2. Test function: Rastrigin’s function

Rastrigin’s function is based on the function of De Jong with the addition of cosine modulation in order to produce frequent local minima. Thus, the test function is highly multimodal. However, the locations of the minima are regularly distributed. The function has the following definition:

\[ f(x) = 10n + \sum_{i=1}^{n} \left[ x_i^2 - 10\cos(2\pi x_i) \right] \]  

(7)

Test area is usually restricted to hyper cube subjected to -5.12 \leq x_i \leq 5.12, i = 1, \ldots, n. Global minimum \( f(x) = 0 \) is obtainable for \( x_i = 0, \ i = 1,2,\ldots,n \).

5.1.3. Test function: Ackley’s function

Ackley’s is a widely used multi-modal test function. It has the following definition:

\[ f(x) = -a \exp \left( -b \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) \]

\[ -\exp \left( \frac{1}{n} \sum_{i=1}^{n} \cos(cx_i) \right) + a + \exp(1) \]  

(8)

It is recommended to set \( a = 20, b = 0.2, c = 2\pi \). Test area is usually restricted to hyper cube constrained as \( 32.768 \leq x_i \leq 32.768, \ i = 1, \ldots, n \). Its global minimum \( f(x) = 0 \) is obtainable for \( x_i = 0, \ i = 1,2,\ldots,n \).

5.1.4. Test function: Rosenbrock’s valley

Rosenbrock’s valley is a classic optimization problem, also known as banana function or the second function of De Jong. The global optimum lies inside along, narrow, parabolic shaped flat valley. To find the valley is trivial, however convergence to the global optimum is difficult and hence this problem has been frequently used to test the performance of optimization algorithms. Function has the following definition:

\[ f(x) = \sum_{i=1}^{n} \left[ 100(x_{i+1} - x_i^2)^2 + (1-x_i)^2 \right] \]  

(9)

Test area is usually restricted to hyper cube subjected to -2.048 \leq x_i \leq 2.048, i = 1, \ldots, n. Global minimum \( f(x) = 0 \) is obtainable for \( x_i = 0, \ i = 1,2,\ldots,n \).

5.1.5. Test function: Easom’s function

The Easom function is a uni-modal test function, where the global minimum has a small area relative to the search space. The function was inverted for minimization. It has only two variables and the following definition:

\[ f(x) = -\cos(x_i)\cos(x_j) \exp\left[-\left((x_i - \pi)^2 + (x_j - \pi)^2\right)\right] \]  

(10)

Test area is usually restricted to square -100 \leq x_i \leq 100, -100 \leq x_j \leq 100. Its global minimum equal \( f(x) = -1 \) is obtainable for \( (x_1, x_2) = (\pi, \pi) \).

5.1.6. Test function: Modified Himmelblau Function

The modified Himmelblau Function is a multi-modal function having four minimum and a global minimum. It has only two variables and the following definition:

\[ f(x_1, x_2) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2 \]

\[ + 0.1 \left[ (x_1 - 3)^2 + (x_2 - 2)^2 \right] \]  

(11)

with respect to \( x_1 \) and \( x_2 \) subject to \( -6 < x_1 < 6 \) and \( -6 < x_2 < 6 \). The function has global minimum of \( f(x) = 0 \) at \( x_1 = 3 \) and \( x_2 = 2 \).

5.2. Experimental on benchmarking functions

The general performance of the competitive algorithms is investigated on the standard benchmarking functions. The optimization problem is concerned with the minimization of the fitness function. For fair comparison all test functions are optimized with the competitive algorithms with same set of population using same random seed. The algorithm is iterated for fixed number of iterations with same population size. The parameters of the competitive algorithms were tabulated in appendix A.

6. Conclusions

The evolutionary hybrid Genetic-Firefly algorithm is implemented and validated in the present context. From the convergence characteristics of the various benchmarking test functions, it is inferred that the proposed Hybrid GA-FA algorithm converges to the optimal solution within less number of iterations when compared with the individual strategy. The convergence characteristics also show the ability of the algorithm to find the precise optimal solution when compared with genetic and firefly algorithms individually. In the hybrid algorithm the Genetic algorithm searches the solution space for global minimum and the Firefly algorithm improves the precession of the potential candidate solution and makes a balance between global and local search. The proposed algorithm explores and exploits the advantages of individual strategies of genetic algorithms “Survival of fitness” and firefly algorithms “Swarm behaviour” and thus emerges as a promising efficient algorithm compared to that of the individual strategy.
Table 1: General performance of competitive evolutionary algorithms against the test functions

<table>
<thead>
<tr>
<th>Test function</th>
<th>Optimal solution and global minimum by the competitive algorithms</th>
<th>De Jong’s function</th>
<th>Rastrigin’s function</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Genetic algorithm</td>
<td>Firefly algorithm</td>
<td>Hybrid Genetic-Firefly algorithm</td>
</tr>
<tr>
<td></td>
<td>f(x₁, x₂) = 0</td>
<td>f(x₁, x₂) = 0</td>
<td>f(x₁, x₂) = 0</td>
</tr>
<tr>
<td></td>
<td>Gen tic algorithm</td>
<td>Firefly algorithm</td>
<td>Hybrid Genetic-Firefly algorithm</td>
</tr>
<tr>
<td></td>
<td>x₁= 0, x₂= 0, f(x₁, x₂) = 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>x₁= 0.0156, x₂= 0.0090, f(x₁, x₂) = 0.0003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>x₁= 0.2625 x 10⁻³, x₂= -0.0531 x 10⁻³, f(x₁, x₂) = 7.1715 x 10⁻⁸</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>x₁= 0.8691 x 10⁻³, x₂= 0.8417 x 10⁻⁴, f(x₁, x₂) = 1.4639 x 10⁻¹⁴</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>x₁= 0.0313, x₂= 0.0871, f(x₁, x₂) = 0.0091</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>x₁= 0.2819, x₂= -0.0188, f(x₁, x₂) = 0.0846</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>x₁= 0.3564 x 10⁻⁸, x₂= 0.7839 x 10⁻⁵, f(x₁, x₂) = 7.8613 x 10⁻¹¹</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 1. 2D plot of function f(x₁, x₂) = x₁² + x₂²

Fig. 2. Convergence characteristics for De Jong’s function

Fig. 3. 2D plot of the function

f(x) = 10⁻⁶ [2 + [x₁² - 10cos(2πx₁)] + [x₂² - 10cos(2πx₂)]]

Fig. 4. Convergence characteristics for Rastrigin’s function
### Ackley’s function

Optimal solution and global minimum for Ackley’s function

\[ x_1 = 0, \]
\[ x_2 = 0, \]
\[ f(x_1, x_2) = 0 \]

![Fig. 5. 2D plot of the function for Ackley’s function](image)

\[ f(x) = -20 \exp(-0.2 \sqrt{x_1^2 + x_2^2}) - \exp\left(\frac{1}{2} (\cos(2\pi x_1) + \cos(2\pi x_2)) + 20 + \exp(1)\right) \]

### Rosenbrock’s valley

Optimal solution and global minimum for Rosenbrock’s function

\[ x_1 = 1, \]
\[ x_2 = 1, \]
\[ f(x_1, x_2) = 0 \]

![Fig. 7. 2D plot of the function for Rosenbrock’s function](image)

\[ f(x) = 100(x_1^2 - x_2)^2 + (1 - x_2)^2 \]

### Convergence characteristics

![Fig. 6. Convergence characteristics for Ackley’s function](image)

![Fig. 8. Convergence characteristics for Rosenbrock’s function](image)
Easom’s function

Optimal solution and global minimum for Easom’s function

\[ x_1 = 3.1416, \]
\[ x_2 = 3.1416, \]
\[ f(x_1, x_2) = -1 \]

Modified Himmelblau Function

Optimal solution and global minimum for Modified Himmelblau Function

\[ x_1 = 3, \]
\[ x_2 = 2, \]
\[ f(x_1, x_2) = 0 \]
Appendix – A: Parameters of Evolutionary Algorithms

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Genetic Algorithm</th>
<th>Firefly Algorithm</th>
<th>Hybrid Genetic-Firefly Algorithm</th>
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<tbody>
<tr>
<td>Population size</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Maximum number of iterations/ generations</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Crossover</td>
<td>Yes, Arithmetic</td>
<td>. . .</td>
<td>Yes, Arithmetic</td>
</tr>
<tr>
<td>Crossover probability (p_c)</td>
<td>0.9</td>
<td>. . .</td>
<td>0.9</td>
</tr>
<tr>
<td>Mutation</td>
<td>Yes, Uniform</td>
<td>. . .</td>
<td>Yes, Uniform</td>
</tr>
<tr>
<td>Mutation probability (p_m)</td>
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<td>. . .</td>
<td>0.1</td>
</tr>
<tr>
<td>Elitism</td>
<td>Yes</td>
<td>. . .</td>
<td>Yes</td>
</tr>
<tr>
<td>No. of Elite solutions</td>
<td>2</td>
<td>. . .</td>
<td>2</td>
</tr>
<tr>
<td>Light absorption coefficient γ</td>
<td>. . .</td>
<td>1.25</td>
<td>1.25</td>
</tr>
<tr>
<td>Attractiveness (β)</td>
<td>. . .</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Randomness (α)</td>
<td>. . .</td>
<td>0.25</td>
<td>0.25</td>
</tr>
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</table>

References


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