Swarm Programming Using Moth-Flame Optimization and Whale Optimization Algorithms

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Abstract Automatic programming (AP) is an important area of Machine Learning (ML) where computer programs are generated automatically. Swarm Programming (SP), a newly emerging research area in AP, automatically generates the computer programs using Swarm Intelligence (SI) algorithms. This paper presents two grammar-based SP methods named as Grammatical Moth-Flame Optimizer (GMFO) and Grammatical Whale Optimizer (GWO). The Moth-Flame Optimizer and Whale Optimization algorithm are used as search engines or learning algorithms in GMFO and GWO respectively. The proposed methods are tested on Santa Fe Ant Trail, quartic symbolic regression, and 3-input multiplexer problems. The results are compared with Grammatical Bee Colony (GBC) and Grammatical Fireworks algorithm (GFWA). The experimental results demonstrate that the proposed SP methods can be used in automatic computer program generation.

Keywords Automatic Programming · Swarm Programming · Moth-Flame Optimizer · Whale Optimization Algorithm

1 Introduction

Automatic programming [1] is a machine learning technique by which computer programs are generated automatically in any arbitrary language. SP [3] is an automatic programming technique which uses SI algorithms as search engine or learning algorithms. The grammar-based SP is a type of SP in which Context-free Grammar (CFG) is used to generate computer programs in a target language. Genetic Programming (GP) [2] is an evolutionary algorithm...
in which tree-structured genome is used to represent a computer program and Genetic algorithm (GA) is used as a learning algorithm. Grammatical Evolution (GE) \[4\],[5] is a variant of grammar-based GP (GGP) \[6\] in which linear genome i.e., array of integer codons is used to represent a genotype and Backus-Naur Form (BNF) of CFG is used to generate the computer programs (i.e., phenotype) from the genotype. Generally, variable-length GA is used as a learning algorithm in GE. SP uses GP-like tree-structure genome which represents a computer program and SI algorithms are used as learning algorithms. O. Roux and C. Fonlupt \[7\] proposed ant programming in which ant colony optimizer (ACO) \[8\] was used to generate the computer programs. D. Karaboga et al. \[9\] proposed artificial bee colony programming (ABCP) for symbolic regression and artificial bee colony (ABC) algorithm \[10\] was used as learning algorithm. A. Mahani and H. Nezamabadi-pour \[11\] proposed Gravitation Search Programming (GSP) in which Gravitation Search Algorithm (GSA) \[12\] was used as a learning algorithm. The grammar-based SP are the variants of GE where SI algorithms are used as search engines or learning algorithms through genotype-to-phenotype mapping using BNF of CFG. Grammatical Swarm (GS) \[13\],\[14\],\[15\], Grammatical Bee Colony (GBC) \[17\], and Grammatical Fireworks algorithm (GFWA) \[18\] are grammar-based SP. Particle Swarm Optimizer (PSO) \[16\] was used as search engine in GS. ABC algorithm was used as search engine in GBC and Fireworks algorithm (FWA) \[19\] was used as search engine in GFWA. Till date, as per author's best knowledge, Moth-Flame Optimization (MFO) \[20\] and Whale Optimization algorithm (WOA) \[21\] are not used in automatic programming. Therefore, in the current work, two grammar-based SP algorithms GMFO and GWO are proposed. In GMFO algorithm, MFO algorithm is used as a search engine to generate computer programs automatically through genotype-to-phenotype mapping using BNF of CFG. Similar to GMFO, WOA is used as a search engine in GWO for automatic computer program generation. The proposed two methods are applied to Santa Fe Ant Trail, symbolic regression and 3-input multiplexer problem. The results of GMFO and GWO are compared to the results of GFWA and GBC. The experimental results demonstrates that the proposed two methods can be used in automatic computer program generation in any arbitrary language.

2 Materials & Methods

In this work, two grammar-based SP such as GMFO and GWO are proposed. In GMFO, MFO algorithm is used as a search engine or learning algorithm to generate computer programs automatically through genotype-to-phenotype mapping. In GMFO, each individual is an array of integer codons in the range \([0, 255]\) and it represents the genotype and derived computer program from genotype using BNF of CFG is known as phenotype. First of all, it is primary concern to define problem specific CFG in BNF. An example of CFG in BNF is given below:
1. \[ \text{<expr> := (<expr><op><expr>) (0) | <var> (1)} \]
2. \[ \text{<op> := + (0) | - (1) | * (2) | / (3)} \]
3. \[ \text{<var> := x1 (0) | x2 (1)} \]

The \(i\)th individual of the search engine, i.e., set of \(d\) integer codons \(X_i(x_1, x_2, \ldots, x_d)\) are initialized as follows:

\[ x_j = \text{round}(255 \times \text{rand}(0, 1)) \]  

A mapping process maps the rule numbers from the codons in the derivation process of computer programs in the following way: \(\text{rule}=(\text{codon integer value}) \mod (\text{number of rules for the current non-terminal})\)

The representation of genotype, phenotype and genotype-to-phenotype mapping are given in Figure 1. Similar to GMFO, the positions of whale are the set of integer codons in the range \([0, 255]\). The same genotype-to-phenotype mapping process as in GMFO is used to generate the computer programs. During the derivation process, if the derivation is run out of codons, then the process restarts from the beginning. This process is called as wrapping. After a certain number of wrapping, if there is any non-terminal remain in the derived program, then the corresponding individual is denoted as invalid. The invalid individual is replaced by the valid individual later on during the search process.

Search engine or learning algorithms are another important part of GMFO and GWO. As already mentioned before, MFO and WOA are used as search engines in GMFO and GWO respectively. MFO algorithm is based on the transverse orientation, i.e., the navigation method of moths in nature. Moths fly in the night by maintaining a fixed angle with respect to the moon for travelling in a straight line for long distance. But they are trapped in a useless or deadly spiral around the artificial light source. This phenomena is modelled in MFO algorithm. The detail description of MFO algorithm can be obtained from [20]. WOA is another nature-inspired meta-heuristic algorithm which mimics the social behaviour of humpback whales. The humpback whales live alone or in group and their favourite prey is krill and small fish herds. Their foraging behaviour, i.e., bubble-net feeding method is done by creating bubbles along a circle. The Bubble-net attacking method (i.e., exploitation phase) has two steps namely shrinking encircling mechanism and spiral updating position. The searching mechanism for prey is used to create exploration of the search space. The detail of WOA can be obtained from [21].

3 Experimental Setup

3.1 Benchmark Problems

Three benchmark problems such as Santa Fe Ant Trail (SFAT), symbolic regression, and 3-input multiplexer are chosen for the experiment. The objective
of the SFAT problem is to find out the program by which an ant can eat 89 piece of food placed in $32 \times 32$ grid in 600 time steps. The target function for symbolic regression problem is $f(x) = x + x^2 + x^3 + x^4$ and 100 fitness cases are generated randomly in the range [-1,1]. 3-input multiplexer problem has 8 fitness cases. The detail descriptions and problem specific defined grammar can be obtained from [17],[18].

3.2 Parameters Settings

The parameters of GMFO are set as the following: number of search agents ($N$) = 30, dimension = 100. The parameters of GWO are set as the following:
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number of search agents \( (N) \) = 30, dimension = 100. The other parameters in GMFO and GWO are dynamically controlled as in [20,21]. As the functions are not evaluated for invalid individual in the above algorithms, the maximum number generations or iterations are not fixed for the comparative study. Therefore, each of GFW, GBC, GMFO, and GWO algorithms is allowed to run for maximum 30,000 number of function evaluations (FEs) in a single run. All algorithms are terminated when they reach the maximum FEs or target error. The target errors are set to 0, 0.01 and 0 for ant trail, symbolic regression and 3-multiplexer problems respectively. The numbers of wrapping are set to 3, 2 and 1 for ant trail, symbolic regression and 3-multiplexer problems respectively.

3.3 PC Configuration

– Operating System: Windows 10 Pro
– CPU: Intel(R) Core(TM) i7-9700K @3.6GHz
– RAM: 64 GB
– Software: Matlab 2018a

4 Results & Discussion

The proposed GMFO and GWO algorithms are applied to Santa Fe Ant Trail (SFAT), symbolic regression, and 3-input multiplexer problems. The experiments are repeated for 30 times independently for each algorithms. The mean and standard deviation of best-run-errors over 30 independent runs are given in Table 1. The number of successful runs and success rates (in %) over 30 independent runs are given in Table 2. The success rate (SR) is calculated as follows:

\[ SR = \frac{\text{number of achieving the target}}{\text{number of total runs}} \]

The number of successful runs and success rates (in %) over 30 independent runs are given in Table 3. The results of GFWA and GBC are obtained from study [18] as the current work is the part of the same project.

| Algorithms | Santa Fe Ant Trail | Symbolic Regression | 3-Multiplexer |
|------------|--------------------|---------------------|---------------|
| GFWA       | 24.57(16.9516)     | 6.65 (7.246)        | 0.93(0.2537)  |
| GBC        | 32.57(17.8609)     | 10.35(7.1404)       | 0.7(0.4661)   |
| GMFO       | 35.53(22.8212)     | 10.35(7.814)        | 0.8(0.407)    |
| GWO        | 23.57(17.2880)     | 10.15(7.4338)       | 1.00(0.00)    |

From Table 1 it is observed that the GWO performs better than other algorithms for SFAT problem. GFWA performs better than other algorithms
Table 2  Number of successful runs and success rates (in %) over 30 independent runs.

| Algorithms | Santa Fe Ant Trail | Symbolic Regression | 3-Multiplexer |
|------------|--------------------|---------------------|---------------|
| GFWA       | 1(3.33%)           | 15(50.00%)          | 2(6.67%)      |
| GBC        | 0(0.00%)           | 7(23.33%)           | 9(30.00%)     |
| GMFO       | 2(6.67%)           | 9(30.00%)           | 6(20.00%)     |
| GWO        | 1(3.33%)           | 9(30.00%)           | 0(0.00%)      |

Table 3  Mean and standard deviation of FEs over 30 independent runs

| Algorithms | Santa Fe Ant Trail | Symbolic Regression | 3-Multiplexer |
|------------|--------------------|---------------------|---------------|
| GFWA       | 29917(453.88)      | 23943(8657.80)      | 29062(4415.30)|
| GBC        | 30000(0.00)        | 27076(6935.20)      | 23549(10420.00)|
| GMFO       | 28224.9(6812.3395) | 21586.9(13097.6074) | 26200(9020) |
| GWO        | 29553.8(2524.6001) | 22432.07(12023.5602) | 30000(0.00) |

For symbolic regression problem, GBC performs better than others for 3-multiplexer problem. If the results of GMFO are compared with GWO, it can be observed that GWO provides a higher accuracy than GMFO for SFAT and symbolic regression problems whereas GMFO provides higher accuracy than GWO only for 3-multiplexer problem.

From Table 2, it is observed that the success rate of GMFO is higher than all others algorithms for SFAT problem. GFWA provides higher success rate than others for regression problem whereas GBC provides higher success rate than others for multiplexer problem. If the success rates of GMFO and GWO are compared, then it can be observed that GMFO has higher success rate than GWO for SFAT and multiplexer problems and there is a tie for regression problem.

From Table 3, it is observed that the mean FEs taken by GMFO is lower than other algorithms for SFAT and regression problems whereas the mean FEs taken by GBC is lower than others for multiplexer problem. The computer programs evolved by GMFO and GWO are given below:

The successful ant program evolved by GMFO (ant eats all 89 pieces of food):

```cpp
if(foodahead()) if(foodahead()) if(foodahead()) if(foodahead())
if(foodahead()) if(foodahead()) move(); else
if(foodahead()) if(foodahead()) left(); else
if(foodahead()) if(foodahead()) left(); else
left(); end; else if(foodahead()) right();
else if(foodahead()) if(foodahead()) if(foodahead())
left(); else left(); end; else move(); end; else move(); end; end; end; else if(foodahead())
if(foodahead()) if(foodahead()) if(foodahead())
if(foodahead()) right(); else left(); end; else left();
end; else move(); end; else left(); end; else move();
end; end; end; else right(); end; else if(foodahead())
move(); else move(); end; end; else left(); end; else
```
left(); end; move(); left(); if(foodahead()) move();
else if(foodahead()) right(); else right(); end; end; right();

The ant program evolved by GWO (ant eats 88 out of 89 pieces of food):
if(foodahead()) left(); else right(); end; right();
if(foodahead()) move(); else left(); end; move(); left();

A successful program evolved by GMFO for symbolic regression problem (absolute error = $1.7837e-15$):
\[
\text{plus}(\text{times}(x, \text{plus}(\text{times}(x, \text{plus}(\text{times}(x, \text{times}(\text{pdivide}(x, x), x))), x)), x)), x)
\]

A successful program evolved by GWO for symbolic regression problem (absolute error = $4.6668e-15$):
\[
\text{times}(\text{plus}(\text{plus}(\text{times}(\text{minus}(\text{times}(x, x), \text{pdivide}(x, x)), x), x), x), x), \text{times}(x, \text{pdivide}(x, x)))
\]

A successful program evolved by GMFO for 3-multiplexer problem (absolute error = 0):
\[
\text{nor}(\text{nor}(\text{nor}(x_3, x_1), \text{nor}(\text{nor}(x_1, \text{nor}(x_1, x_1)), x_2)), \text{nor}(\text{nand}(\text{nor}(x_2, x_1), \text{nor}(x_1, x_1)), x_3))
\]

A program evolved by GWO for 3-multiplexer problem (absolute error = 1):
\[
\text{nand}(\text{or}(x_3, x_1), x_2)
\]

From the discussion of the results, it is found that no single algorithm performs better than all other algorithms for all problems in this study. The above presented results are the experimental evidence of the fact that the proposed GMFO and GWO algorithms can be used in automatic computer program generation in any arbitrary language.

5 Conclusion

This paper presents two grammar-based swarm programming methods namely GMFO and GWO. The proposed methods are applied to solve SFAT, symbolic regression, and 3-input multiplexer problems. The experimental results demonstrate that the proposed methods can be used to generate computer programs automatically in any arbitrary language. In this study, the basic version of MFO and WOA are utilized as search engines or learning algorithms in genotype-to-phenotype mapping. The update version of these algorithms can be used to obtain better performance in automatic computer program generation. In the future, the GMFO and GWO can be applied to real-world problems such as data classification and regression analysis.
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