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A novel hybrid meta-heuristic algorithm for optimization problems

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ABSTRACT
This paper presents a novel hybrid meta-heuristic algorithm called HMGSG to solve the optimization problems. In the proposed HMGSG algorithm, a spiral-shaped path for grey wolf optimization (GWO) is used to ensure both the faster convergence rate and diversity. The mutualism phase of symbiotic organisms search (SOS) is introduced and modified with the adaptive benefit factors to optimize the ability of exploitation. The stud genetic algorithm (GA) is introduced into the HMGSG to promote convergence. The numerical experiment results show that the performance of HMGSG is superior to that of the GWO, SOS and GA. In addition, the HMGSG algorithm is used to optimize the fractional-order PID controller parameters for roll attitude control of UAV. And the simulation results show the effectiveness of this algorithm.

1. Introduction
Optimization is an important research field, and solving optimization problems is a challenging issue. Many traditional methods are not adequate to solve complex optimization problems, especially for those which have higher dimensions or more than one local optimum (Farnad, Jafarian, & Baleanu, 2018). Therefore, many researchers have a great interest in meta-heuristic algorithms during the recent years (Duan, 2015). Many meta-heuristic algorithms are nature-inspired (Manjarres, Landa-Torres, & Gil-Lopez, 2013), which means that they are originated from mimicking physical phenomena or the interactive behaviours of the organisms. Meta-heuristic optimization algorithms can solve the complex optimization problems and search for a set of relevant parameter values by minimizing or maximizing the objective functions (Faris, Sheta, & Öznergiz, 2016). There are many famous meta-heuristic algorithms which include genetic algorithm (GA) (Mousavi-Avval, Rafiee, Sharifi, Hosseinpour, & Notarnicola, 2017; Rajarathinam, Gomm, Yu, & Abdelhadi, 2017), particle swarm optimization (PSO) algorithm (Chen et al., 2014; Satpati, Koley, & Datta, 2014), differential evolution (DE) algorithm (Long, Liang, Huang, & Chen, 2013; Piotrowski, 2016), ant colony optimization (ACO) (Chen, Zhou, & Luo, 2017; Samà, Pelligrini, D’Ariano, Rodriguez, & Pacciarelli, 2016), artificial bee colony (ABC) algorithm (Li, Gong, & Yang, 2014; Xue, Jiang, Zhao, & Ma, 2018), and gravitational search algorithm (GSA) (Mirjalili & Gandomi, 2017; Rashedi, Nezamabadi-Pour, & Saryazdi, 2011).

Grey wolf optimization (GWO) algorithm, which was a new swarm intelligence algorithm based on the behaviour of grey wolves for global optimization, was proposed by Mirjalili (2014). This algorithm mimics the hunting behaviour and the social leadership of grey wolves. Compared with other meta-heuristic algorithms, the GWO has the advantages of flexibility, simplicity and implementation. As an efficient and competitive optimization algorithm, the GWO has been applied to solve many engineering applications and control problems, such as economic load dispatch problems (Pradhan, Roy, & Pal, 2016), PID controller design (Oliveira, Freire, & Pires, 2016), load frequency control of interconnected power system (Guha, Roy, & Banerjee, 2016), wide-area power system stabilizer design (Shakarami & Davoudkhani, 2016), battery energy storage device (Sharma, Bhattacharjee, & Bhattacharya, 2016), and unmanned combat aerial vehicle path planning (Zhang, Zhou, Pan, & Pan, 2016). However, the optimization pattern of the GWO algorithm may lead the entire group fall into the local optimum, and a lack of diversity would occur in the population.

In recent years, some researchers have investigated a new kind of technique called hybridization (Thangaraj, Pant, Abraham, & Bouvry, 2011), which is a combination of the meta-heuristic algorithm with other algorithmic
components for optimization. In this technique, the skilled combination can display the more efficient optimization for dealing with the practical problems. In hybrid optimization algorithms, many combinations of famous optimization methods have been developed. Tawhid and Ali (2017) combined the GWO algorithm with genetic algorithm for finding the minimum value of the potential energy function. They divide the population into groups to assure a good coverage of the searching operation. Kamboj (2015) developed a novel hybrid PSO–GWO approach for unit commitment problem. The effectiveness of the hybrid PSO–GWO algorithm is compared with classical PSO, PSOLR, HPSO and various other hybrid algorithms. Jayabarathi and Raghunathan (2016) presented a new hybrid algorithm to solve the economic dispatch (ED) problem for better performance. The GWO algorithm is hybridized by combining the operators of mutation and crossover from evolutionary algorithms (EA’s). Jiang, Ji, and Shen (2014) established a novel optimization algorithm HPSO–GSA to solve the economic emission load dispatch (EEDL) problems. They achieve an efficient balance between the social essence of PSO and the Newtonian gravity concept of GSA. Kefayat, Ara, and Niaki (2015) presented a hybrid ACO–ABC algorithm by combining ant colony optimization (ACO) with artificial bee colony (ABC) algorithm to optimal location and sizing of distributed energy resources (DERs). This hybrid ACO–ABC algorithm owns the global search ability and the local search ability simultaneously. In addition, they use a multi-objective ABC to produce a set of non-dominated solutions in the proposed algorithm. Mahi, Baykan, and Kodaz (2015) presented a hybrid algorithm with PSO, ACO and 3-Opt heuristic method to solve the Travelling Salesman Problem (TSP). This combination reduces the probability of falling in local minimization and premature convergence. Soleimani and Kannan (2015) proposed a new hybrid meta-heuristic algorithm that is made up of the GA and PSO. They analyse this two algorithm’s superiority and weaknesses and attempt to modify the traditional genetic algorithm by the particle swarm optimization. In addition, they use CPLEX and MATLAB software to finish a complete validation process. However, these hybrid algorithms are just the simple combination of the basic algorithms, without performance improvement for the basic algorithms.

Currently, the controller design of unmanned aerial vehicles (UAVs) has attracted great attention of researchers and developers around the world (Tavakol & Binazadeh, 2017). And a stable and robust attitude controller in the flight control system is significant for UAVs to finish the desired tasks successfully. Therefore, the fractional-order controller has attracted great attention by many scientists to improve system performance (Kesarkar & Selvaganesan, 2014; Shah & Agashe, 2016; Sheng, Zhang, & Gao, 2014). For example, a roll-channel fractional-order PI controller was designed for small fixed-wing UAV by Chao et al. (2010). They are the first to achieve the fixed-wing UAV flight test successfully with a fractional-order flight controller, and the flight experiment results show that the proposed controller is effective.

Meta-heuristic algorithms need to have an excellent balance between the exploration operation and the exploitation operation to achieve the global and local searches efficiently. Since the previous techniques have shown the superiority in solving optimization problems and improving the balance ability, we have combined modified GWO, SOS and GA, and proposed a novel hybrid optimization algorithm called Hybrid Modified GWO/SOS/GA (named as HMGSG) algorithm. The proposed method contains different innovative concepts, and its great optimization capacity and diversity can help to solve the fractional-order PID controller parameters optimization problem for UAV attitude control. The main innovations of this paper are summarized as follows:

- A spiral-shaped updating position method has been used in GWO to enhance the diversity of the population.
- The mutualism phase of symbiotic organisms search (SOS) is introduced to avoid the local minima. Especially, an adaptive mechanism is proposed to compute the benefit factors in SOS.
- The stud genetic algorithm has been used to improve the exploration ability and accelerate the convergence process.

The structure of the paper is organized as follows. The principles of the basic grey wolf optimizer are described in Section 2. Section 3 explains the detailed implementation of the proposed HMGSG algorithm. The benchmark functions are used to verify the validity of the proposed algorithm in Section 4. Section 5 introduces the fractional-order PID controller design strategy and Section 6 finishes the flight simulation experiment for roll attitude control of UAV. Finally, Section 7 summarizes the conclusions.

2. The basic GWO algorithm

The GWO algorithm is a novel swarm intelligence approach that can imitate the social hierarchy and hunting pattern of grey wolves in nature. In the basic GWO algorithm, the individual with the best fitness is considered as \( \alpha \) wolf. The second and third individuals with better fitness are considered as \( \beta \) wolf and \( \delta \) wolf. The rest
of the individuals are considered as $\omega$. The social hierarchy of grey wolves is shown in Figure 1.

To imitate the encircling behaviour that the grey wolves hunt the prey, the individuals update their positions as follows:

$$D_i = |C_i \cdot X_p(t) - X_i(t)|$$  \hspace{1cm} (1)$$

$$X_i(t + 1) = X_p(t) - A_i \cdot D_i$$  \hspace{1cm} (2)$$

where $t$ is the current iteration, $X_i$ indicates the position of a grey wolf in the search space, $X_p$ is the position of the prey. $A_i = 2a \cdot r_1 - a$, $C_i = 2 \cdot r_2$, $a = 2 - 2t/t_{\text{max}}$, where $A_i$ and $C_i$ are coefficient vectors. $r_1$ and $r_2$ are random parameters in $[0,1]$, $a$ is linearly decreased from 2 to 0.

It is assumed that the leader group ($\alpha$, $\beta$ and $\delta$) has the better information about the prey location. Therefore, each $\omega$ wolf can update its position according to the best search agents as follows:

$$D_\alpha = |C_1 \cdot X_\alpha(t) - X_i(t)|$$  \hspace{1cm} (3)$$

$$D_\beta = |C_2 \cdot X_\beta(t) - X_i(t)|$$  \hspace{1cm} (4)$$

$$D_\delta = |C_3 \cdot X_\delta(t) - X_i(t)|$$  \hspace{1cm} (5)$$

$$X_1 = X_\alpha(t) - A_1 \cdot D_\alpha$$  \hspace{1cm} (6)$$

$$X_2 = X_\beta(t) - A_2 \cdot D_\beta$$  \hspace{1cm} (7)$$

$$X_3 = X_\delta(t) - A_3 \cdot D_\beta$$  \hspace{1cm} (8)$$

where $X_\alpha$, $X_\beta$, and $X_\delta$ denote the positions of the leader group, $X_i$ is the position of the current solution.

Based on these equations, the basic steps of the grey wolf optimization can be shown in Figure 2.

3. The HMGSG algorithm

3.1. A spiral-shaped path for GWO

According to the detailed study of Section 2, it has been observed that grey wolves have the capability to find the location of the prey and hunt them. However, the location of the optimal value is unknown in the search space. Therefore, to imitate the hunting behaviour mathematically, it is assumed that the grey wolves update their positions affected by the leader group ($\alpha$, $\beta$ and $\delta$). This approach may lead the entire group fall into the local optimum when the current leader is local optimum.

To improve the exploitation ability and enhance the diversity of grey wolves, we are inspired by the whale optimization algorithm (Mirjalili & Lewis, 2016) and use a spiral-shaped updating position method to avoid the local minization and premature convergence. The spiral-shaped path can enhance the ability that the algorithm finds the globally optimal solution, and the excellent individuals will not be destroyed. The spiral-shaped path is formed by the position of wolf and prey as follows:

$$X_i(t + 1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X_p(t)$$  \hspace{1cm} (10)$$

$$D' = |X_p(t) - X_i(t)|$$  \hspace{1cm} (11)$$

where $t$ is the current iteration, $X_i$ indicates the position of a grey wolf, $X_p$ is the position of the prey, $b$ indicates the
shape of the logarithmic spiral, \( l \) is a random parameter in \([-1,1]\).

It should be noted that the grey wolves also need to chase the prey, and not just encircle around it. To imitate the hunting behaviour mathematically, it is assumed that there is a parameter to make the wolves choose one method to update their locations during optimization. The location update equation is as follows:

\[
X_i(t+1) = \begin{cases} 
X_p(t) - A_i \cdot D_i, & \text{if } p > \sigma \\
D_i \cdot e^{bl} \cdot \cos(2\pi l) + X_p(t), & \text{if } p \leq \sigma 
\end{cases} 
\tag{12}
\]

where \( \sigma \) is a random parameters in \([0,1]\).

The pseudocode of the GWO algorithm with the spiral-shaped path is as follows:

| GWO algorithm with spiral-shaped path |
|-------------------------------------|
| **Begin**                          |
| **Step1:** fitness calculating     |
| Calculate and compare the fitness of individuals, determine the current first three best individuals |
| **Step2:** position updating        |
| Update parameters                  |
| for each individual                |
| if \( p > \sigma \)                |
| Update the positions of the current individual by the Eq. (2) |
| else                               |
| Update the positions of the current individual by the Eq. (10) |
| **end for**                        |
| **End**                            |

### 3.2. Modified mutualism phase

The mutualism phase is an important part of SOS algorithm, which benefits two related individuals. In the basic mutualism, \( X_i \) represents the \( i \)th individual in the population, and \( X_j \) is selected randomly to communicate with \( X_i \). Finally, new individuals coming from \( X_i \) and \( X_j \) are generated by these equations:

\[
X_{i\text{new}} = X_i + \text{rand}(0,1) \cdot (X_{\text{best}} - \text{Mutual\_Vector} \cdot BF_1) \\
X_{j\text{new}} = X_j + \text{rand}(0,1) \cdot (X_{\text{best}} - \text{Mutual\_Vector} \cdot BF_2) 
\tag{13}
\]

where \( \text{Mutual\_Vector} = \frac{X_i + X_j}{2} \)

\[
BF_1 = \begin{cases} 
2, & |f_{\text{best}} - f_i| < \varepsilon \\
1 + \frac{1}{|f_{\text{best}} - f_i|}, & \text{else} 
\end{cases} 
\tag{16}
\]

\[
BF_2 = \begin{cases} 
2, & |f_{\text{best}} - f_j| < \varepsilon \\
1 + \frac{1}{|f_{\text{best}} - f_j|}, & \text{else} 
\end{cases} 
\tag{17}
\]

where \( f_{\text{best}} \) is the best fitness of the current population, \( f_{\text{mean}} \) is the average fitness of the current population, and \( \varepsilon \) is accuracy parameters.

The pseudocode of the modified mutualism phase is as follows:

| Modified mutualism phase |
|---------------------------|
| **Begin**                 |
| **Step1:** fitness calculating |
| Calculate and compare the fitness of individuals, find the current first best individual as \( X_{\text{best}} \) |
| **Step2:** mutualism operator |
| for each individual \( X_i \) |
| Select \( X_i \) randomly |
| Calculate \( X_{i\text{new}} \) and \( X_{j\text{new}} \) by the Eq. (13) and the Eq. (14) |
| if \( X_{i\text{new}} \) fitness better than \( X_i \) |
| Update \( X_i \) positions with \( X_{i\text{new}} \) |
| else |
| if \( X_{j\text{new}} \) fitness better than \( X_j \) |
| Update \( X_j \) positions with \( X_{j\text{new}} \) |
| **end for**               |

### 3.3. Stud genetic algorithm

The stud genetic algorithm is an improvement of the traditional genetic algorithm. The stud individual (or the current optimal individual) is used for mating with other individuals in the population (Ganapathy, Kumar, & Jerome, 2014). This behaviour can help the population generate the better solutions for each iteration process. In the stud GA, there are three main steps called selection, crossover and mutation. Firstly, the selection operation is used to find the stud and a random individual as parents. Then the crossover operation is completed for generating a new offspring, which can accelerate the convergence process.
Finally, the mutation operation has been introduced to enhance the diversity. The general procedure for the stud GA is as follows:

**Stud genetic algorithm**

Begin

Step 1: fitness calculating
Calculate and compare the fitness of individuals, find the current first best individual as stud

Step 2: crossover and mutation operation
for each selected individual $X_i$ (by the probability $p_c$)
Generate offspring by the mating of $X_i$ and stud

end for

perform mutation operator by the probability $p_m$

Step 3: judgement
for each offspring generated by crossover and mutation operation

if (offspring fitness better than old)
Update old positions with offspring

end if

end for

End

3.4. The proposed HMGSG algorithm

The structure flowchart of the proposed HMGSG is as follows:

![Flowchart of the HMGSG algorithm](image)

**Figure 3.** Flowchart of the HMGSG algorithm.

The Figure 3 shows that there are four parts in the HMGSG algorithm. After initializing parameters in Part 1, the individuals update their positions by a spiral-shaped path for GWO to ensure both convergence and diversity in Part 2. Then we apply the modified mutualism phase to optimize the ability of exploitation in Part 3. Finally, the stud genetic algorithm has been used to accelerate the convergence process in Part 4.

4. Numerical experiment results

In this paper, the five benchmark test functions are used to show the performance of the HMGSG algorithm. A comparison has been performed with the basic GWO, SOS and GA algorithm. These benchmark functions are listed in Table 1.

The parameter settings for HMGSG are as follows: the population size is set as 40, and the maximum iteration is set as 400. On the setting of control parameters, the accuracy parameters $\epsilon = 1$, the crossover probability $p_c = 0.5$, the mutation probability $p_m = 0.1$. For each benchmark function, 30 independent runs are performed from different populations which are generated randomly. In addition, we record the average value and standard deviation as Ave and Std. These comparison results are listed in Table 2.

In Table 2, it is obvious that the HMGSG owns the better average and standard deviation on the function $F_1$, $F_2$, $F_4$, $F_5$. The HMGSG couldn’t get the superiority only in $F_3$. In addition, the standard deviation of the HMGSG algorithm is particularly small, which indicates that the HMGSG has a great robustness.

The convergence curves of five benchmark functions are shown in Figure 4. The HMGSG algorithm has the faster convergence rate, the higher convergence accuracy and the less iteration rate in contrast to the other algorithms in the five benchmark functions. Therefore,

---

**Table 1.** Benchmark functions.

| Function | Range      | $F_{\text{min}}$ |
|----------|------------|-----------------|
| $F_1(x) = \sum_{i=1}^{n} x_i^2$ | $[-100, 100]$ | 0 |
| $F_2(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i|$ | $[-10, 10]$ | 0 |
| $F_3(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i)^2 + (x_i - 1)^2]$ | $[-20, 20]$ | 0 |
| $F_4(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10)$ | $[-5.12, 5.12]$ | 0 |
| $F_5(x) = -20 \exp(-\frac{1}{\pi} \sum_{i=1}^{n} x_i^2) - \exp\left(\frac{1}{\pi} \sum_{i=1}^{n} \cos(2\pi x_i)\right) + 20 + e$ | $[-32, 32]$ | 0 |
these results show that the proposed HMGSG has the better performance than the other three methods in exploiting the global optimum and overcoming premature convergence.

5. Fractional-order PID controller

5.1. Fractional-order operators

There are some popular definitions for fractional-order operators including Riemann–Liouville (RL) definition, Caputo definition and Grunwald–Letnikov definition (Kesarkar & Selvaganesan, 2014). The RL fractional integral is expressed as follows:

\[ D_{t}^{-\alpha}f(t) = \frac{1}{\Gamma(\alpha)} \int_{0}^{t} (t - \tau)^{\alpha - 1} f(\tau) d\tau \]  

where \( 0 < \alpha < 1 \), \( \Gamma(\alpha) \) is the Gamma function expressed as:

\[ \Gamma(z) = \int_{0}^{\infty} e^{-t} t^{z-1} dt, \quad Re(z) > 0 \]  

The Laplace transform of the RL fractional operator with zero initial condition could be expressed as:

\[ L[D_{t}^{-\alpha}f(t)] = \frac{1}{s^\alpha} F(s) \]  

where \( F(s) \) is the Laplace transform of \( f(t) \).

5.2. Fractional-order controller

In recent decades, proportional integral derivative (PID) controller has been used widely in industries (Shah & Agashe, 2016). The reason that PID controller becomes so popular lies in the good control performance and the simplicity of design for the controlled plants. The fractional PID controller (FOPID) is an extension of the traditional PID controller which introduces the fractional derivative and integral operation. The fractional-order controller has provided the additional design freedom, and has the better performance in the high order systems, long delayed-time system and nonlinear system.

The typical fractional-order controller \( C(s) \) found in the literature (Shah & Agashe, 2016) is as follows:

\[ C(s) = K_p + \frac{K_0}{s^\mu} + K_ds^\lambda, (\lambda, \mu \geq 0) \]  

where \( K_p \) is the proportional gain, \( K_0 \) is the integration gain, \( K_d \) is the derivative gain, \( \lambda \) and \( \mu \) are the order of integration and differentiator.

As shown in Figure 5, the traditional PID controller is the special cases of the fractional PID controller. Compared with the PID controller that only can jump between four fixed points, it is possible for FOPID to move randomly in the field of definition. In general, the range of \( \lambda \) and \( \mu \) are limited in \([0,2]\).

6. FOPID experiment results

The UAV model is a linear six degrees of freedom model and has been established by Gai and Wang (2013). The initial speed and altitude are set as 190 m/s and 6000 m. The closed loop feedback system is shown in Figure 6.

In this experiment, the performance index using the ITSE method is as follows:

\[ J = \int_{0}^{\infty} t \cdot e^2(t) dt \]
The HMGSG algorithm is used to optimize the parameters of the traditional PID and FOPID. To show the superiority of the proposed algorithm, the comparative results with the classical GWO algorithm are also given. The optimization results are shown as Tables 3 and 4, and the convergence curves are shown as Figures 7–8.

The HMGSG algorithm has the faster convergence speed and the smaller fitness value in the PID and FOPID parameters optimization of roll attitude control of UAV.

Figure 4. The convergence curves of five benchmark functions (GA, GWO, SOS and HMGSG). (a) F1 with $D = 30$. (b) F2 with $D = 30$. (c) F3 with $D = 30$. (d) F4 with $D = 30$. (e) F5 with $D = 30$.

The simulation results are shown as Figures 9–10 and Table 5.

In Figures 7 and 8, compared with the GWO algorithm, the HMGSG algorithm has the faster convergence speed and the smaller fitness value in the PID and FOPID parameters optimization of roll attitude control of UAV.
Figure 5. Fractional PID controller domain.

Figure 6. FOPID flight controller system.

Table 3. Optimization results of FOPID and PID using the HMGSG algorithm.

| Controller | Optimal results         | Cost($/J) |
|------------|-------------------------|-----------|
| PID        | 4.7615 + 0.08557/s + 0.87225s | 1.2282    |
| FOPID      | 4.8842 + 0.8837/s + 1.3827t^1.4536 | 0.7155    |

Table 4. Optimization results of FOPID and PID using the GWO algorithm.

| Controller | Optimal results         | Cost($/J) |
|------------|-------------------------|-----------|
| PID        | 4.9814 + 0.08585/s + 0.76704s | 1.2741    |
| FOPID      | 4.3825 + 0.7777/s + 1.2564t^0.4726 | 1.0225    |

Figure 9 and Table 5 show that the FOPID controller has shorter settling time and smaller overshoot than the traditional PID controller.

To show the superiority of FOPID controller, the wind disturbance is introduced to examine the anti-disturbance ability when the time is 5s. The amplitude of wind disturbance is 10 m/s. And the tracking effect for the roll attitude command is shown in Figure 10 using the FOPID and traditional PID controller. The results show that the FOPID controller has the better dynamic performance and anti-disturbance ability than the traditional PID controller.
7. Conclusions

This paper presents a novel hybrid method named HMGS algorithm, which provides an interesting combination of modified GWO, SOS and GA. To validate the effectiveness of the presented method, the benchmark numerical experiment has been performed. Experiment results show that the proposed algorithm has a more excellent ability of exploration and exploitation than the GA, GWO and SOS algorithms. In addition, based on the parameters tuning method of the proposed algorithm and GWO algorithm, the UAV roll attitude fractional-order PID controller and traditional PID controller are designed with the wind gust response. The experiment results show that the FOPID controller has a shorter settling time and smaller overshoot, and the controllers under the parameters tuning method of the HMGS algorithm have superiority performance.

Disclosure statement

No potential conflict of interest was reported by the authors.

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