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# Literature Review on Grey Wolf Optimization Techniques

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**Abstract:** ***This paper present reviews on various control techniques employed on to Grey Wolf Optimization . The control techniques are studied in general as well as with respect to the field of application. The leadership hierarchy and hunting behaviour of the grey wolves is explained in GWO by developing a mathematical model.***

**Keywords:** Optimization, hunting, Encircling

## 1. Introduction

Grey wolf optimizer (GWO) is a recently proposed intelligent optimization method inspired by hunting behaviour of grey wolves. In GWO algorithm, the parameter of $\vec{a}$ is decreased from 2 to 0 to balance exploitation and exploration, respectively. A novel time-varying parameter of $\vec{a}$ decreasing linearly is used to enhance the performance of GWO algorithm. In order to enhance the global convergence, when generating the initial population, the good-point-set method is employed.

Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented. The algorithm is then benchmarked on 29 well-known test functions, and the results are verified by a comparative study with Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Differential Evolution (DE), Evolutionary Programming (EP), and Evolution Strategy (ES). The GWO algorithm is able to provide very competitive results compared to these well-known meta-heuristics. The GWO also considers solving three classical engineering design problems (tension/compression spring, welded beam, and pressure vessel designs) and presents a real application of the proposed method in the field of optical engineering.

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. According to Muro et al.[2] the main phases of gray wolf hunting are as follows:

- Tracking, chasing, and approaching the prey
- Pursuing, encircling, and harassing the prey until it stops moving
- Attack towards the prey

The swarm intelligence algorithms are proposed to mimic the swarm intelligence behaviour of biological in nature, which has become a hot of cross-discipline and research field in recent years. The appearance of swarm intelligent optimization algorithm provides the fast and reliable methods for finding solutions on many complex problems1,2. Because the swarm intelligence algorithm have characteristics of self-organization, parallel, distributive, flexibility and robustness, now they have been very widespread used in many cases, such as electric power system, communication network, system identification and parameter estimation, robot control, transportation and other practical engineering problems3,4,5. Therefore, the research on the swarm intelligence optimization algorithms has an important academic value and practical significance. At present, a variety of swarm intelligence optimization algorithms have been proposed by simulating the biotic population and evolution process in nature, such as particle swarm optimization (PSO) algorithm, shuffled frog leaping algorithm (SFLA), artificial bee colony (ABC) algorithm, ant colony optimization (ACO) algorithm, biogeography-based optimization (BBO) algorithm, and cuckoo search (CS) algorithm. Particle Swarm Optimization (PSO) algorithm put forward by Kennedy and Eberhart to mimic the the foraging behavior of birds and fish flock6, but the convergence velocity and searching accuracy of PSO algorithm are unsatisfactory to some extend. Shuffled Frog-leaping Algorithm (SFLA) put forward by Eusuff in 2003 is a novel swarm intelligent cooperative searching strategy based on the natural memetics7,8. On the one hand, individuals exchange information in the global searching process, and its search precision is high. On the other hand, SFLA has the disadvantage of slow convergence velocity and easy to falling into the local optimum. Artificial Bee Colony (ABC) Algorithm put forward by Karaboga in 2005 to mimics the finding food source behaviour of bees9. In order to mimic the social behaviour of the ant colony, Dorigo *et al*. Proposed the an novel Ant Colony Optimization (ACO) Algorithm in 200610. But their disadvantages are the slow convergence speed and easy to premature. Biogeography-Based Optimization (BBO) algorithm was put forward by Simon in 200811, whose idea is based on the geographical distribution principle in the biogeography. Cuckoo Search (CS) Algorithm was proposed by Yang and Deb in 2009 based on the cuckoo's parasitic reproduction mechanism and Levy flights searching strategy, whose advantage is that CS algorithm is not easy to fall into the local optimum compared with other intelligent algorithms and has less parameters, and whose disadvantage is that the adding of Levy Flight search mechanism leads to strong leap in the process of search, thus, its local search is not careful.

The common shortcoming of these algorithms is that each swarm intelligence algorithm has problem in different degrees that the convergence velocity is slow, the optimization precision is low, and easy to fall into the local optimum5. The key reason cause these shortcoming is that whether an algorithm is able to achieve the proper compromise between exploration and exploitation in its each searching phase or no. Exploration and exploration are contradictory. Exploration reflects the ability of the algorithm to search for new space, while exploration reflects the refining ability of the algorithm. These two criteria are generally used to evaluate stochastic optimization algorithms. Exploration is refers to that a particle leave the original search path in a certain extent and search towards a new direction, which reflects the ability of exploiting unknown regions. Exploitation is refers to that a particle continue to search more carefully on the original trajectory in a certain extent, which can insure the wolf make a detailed search to the region that have been explored. Too small exploration can cause a premature convergence and falling into a local optimum, however, too small exploitation will make the algorithm converge too slowly.

The grey wolf optimizer (GWO) as a novel swarm intelligent optimization algorithm was put forward by Seyedali Mirjalili etc in 2014, which mainly mimics wolf leadership hierarchy and hunting mechanism in nature15. Seyedali and Mirjalili etc has proved that the optimization performance of standard GWO is superior to that of PSO, GSA, DE and FEP algorithm. Due to the wolves algorithm with the advantages of simple in principle, fast seeking speed, high search precision, and easy to realize, it is more easily combined with the practical engineering problems. Therefore, GWO has high theoretical research value. But GWO is as a new biological intelligence algorithm, the research about it is just at the initial phase, so research and development of the theory are still not perfect. In order to make the algorithm plays a more superior performance, further exploration and research is needed.

Many swarm intelligence algorithms are mimic the hunting and searching behaviors of some animals. However, GWO simulates internal leadership hierarchy of wolves, thus, in the searching process the position of best solution can be comprehensively assessed by three solutions. But for other swarm intelligence algorithms, the best solution is searched only leaded by a single solution. So GWO can greatly decrease the probability of premature and falling into the local optimum. So as to achieve the proper compromise between exploration and exploitation, an improved GWO with evolution and elimination mechanism is proposed. The biological evolution and the SOF principle of biological updating of nature are added to the basic wolf algorithm. In order to verify the performance of the improved GWO, 12 typical benchmark functions are adopted to carry out simulation experiments, meanwhile, experimental results are compared with PSO algorithm, ABC algorithm and CS algorithm. The experimental results show that the improved grey wolf optimizer (IGWO) obtains the better convergence velocity and optimization accuracy.

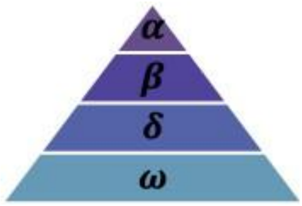
## 2. Literature Review

**Mathematical model**

The hunting technique and the social hierarchy of grey wolves are mathematically modelled in order to design GWO and perform optimization. The proposed mathematical models of the social hierarchy, tracking, encircling, and attacking prey are as follows:

**Social hierarchy**

In order to mathematically model the social hierarchy of wolves when designing GWO, we consider the fittest solution as the alpha (α). Consequently, the second and third best solutions are named beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). In the GWO algorithm the hunting (optimization) is guided by α, β, and δ. The ω wolves follow these three wolves.




**Encircling prey**

Grey wolves encircle prey during the hunt. In order to mathematically model encircling behaviour the following equations are proposed

$$\vec{D} = |\vec{C}.\vec{X_p}(t) - \vec{X}(t)|$$

$$\vec{X}(t+1) = \vec{X_p}(t) - \vec{A}.\vec{D}$$

The vectors are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a}$$

$$\vec{C} = 2.\vec{r_2}$$

**Hunting**

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution) beta and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agent. The following formulas are proposed in this regard



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$$\vec{D}_\alpha = |\vec{C}_1 . \vec{X}_\alpha - \vec{X}|$$

$$\vec{D}_\beta = |\vec{C}_2 . \vec{X}_\beta - \vec{X}|$$

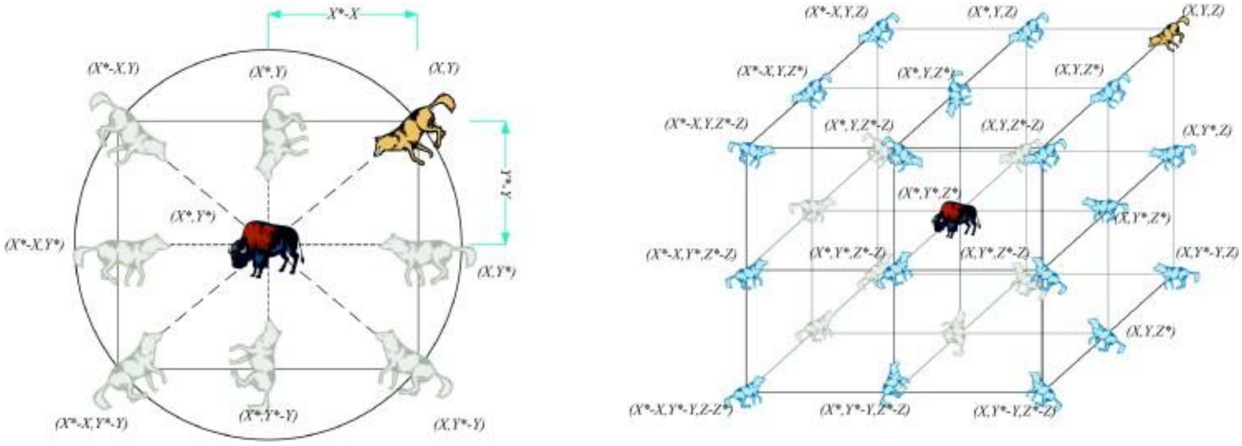
$$\vec{D}_\delta = |\vec{C}_3 . \vec{X}_\delta - \vec{X}|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 . (\vec{D}_\alpha)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 . (\vec{D}_\beta)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 . (\vec{D}_\delta)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$



(a) (b)

**Grey Wolf Optimizer**

The grey wolf optimizer is a novel heuristic swarm intelligent optimization algorithm proposed by Seyedali Mirjalili *et al*. in 2014. The wolf as top predators in the food chain, has a strong ability to capture prey. Wolves generally like social life and in the interior of the wolves exists a rigid social hierarchy.

In order to mimic wolves internal leadership hierarchy, the wolves is divided into four types of wolf: *alpha*, *beta*, *delta* and *omega*, where the best individual, second best individual and third best individual are recorded as *alpha*, *beta*, and *delta*, *and* the rest of the individuals are considered as *omega*. In the GWO, the hunting (optimization) is guided by *alpha*, *beta*, and *delta*8. They guide other wolves (*W*) tend to the best area in searching space. In iterative searching process, the possible position of prey is assessed by three wolves *alpha*, *beta*, and *delta*. In optimization process, the locations of wolves are updated based on Eqs (1) and (2).

D→=|C→·XP−→(t)−X→(t)|D→=|C→·XP→(t)−X→(t)|(1)

X→(t+1)=XP−→(t)−A→·D→X→(t+1)=XP→(t)−A→·D→ (2)

where, *t* represents the *t*-th iteration, A→A→ and C→C→ are coefficient vector, XP−→XP→ is the position vector of prey, X→X→ represents the wolf position. The vector A→A→ and C→C→ can be expressed by:

A→=2a·r1→−a→A→=2a·r1→−a→ (3)
C→=2·r2→C→=2·r2→ (4)

where, the coefficient a→a→ linearly decreases from 2 to 0 with the increasing of iteration number, r1→r1→ and r2→r2→ are random vector located in the scope [0, 1].

Principle of the position updating rules described in Eqs (1) and (2) are shown in Fig. 1. It can be seen from Fig. 1 the wolf at the position (*X*, *Y*) can relocate itself position around the prey according to above updating formulas. Although Fig. 1 only shows 7 positions that the wolf possible move to, by adjusting the random parameters C and A it can make the wolf to relocate itself to any position in the continuous space near prey. In the GWO, it always assumes that position of alpha, beta and delta is likely to be the prey (optimum) position. In the iteration searching process, the best individual, second best individual and third best individual obtained so far are respectively recorded as *alpha*, *beta*, and *delta*. *H*owever, other wolves who are regarded as omega relocate their locations according to the locations of *alpha*, *beta*, and *delta*. The following mathematical formulas are used to re-adjust positions of the wolf *omega*. The conceptual model that wolf update its position is shown in Fig. 2.

D→α=|C1−→·Xα−→−X→|D→α=|C1→·Xα→−X→| (5)
D→β=|C2−→·Xβ−→−X→|D→β=|C2→·Xβ→−X→| (6)
D→δ=|C3−→·Xδ−→−X→|D→δ=|C3→·Xδ→−X→| (7)

where, Xα−→Xα→, Xβ−→Xβ→ and Xδ−→Xδ→ are the position vector of *alpha*, *beta*, and *delta*, respectively. C1−→C1→, C2−→C2→, C3−→C3→ are randomly generated vectors, X→X→ represents the position vector of current individual. The Eqs (5), (6) and (7) respectively calculate the distances between the position of current individual and that of individual *alpha*, *beta*, and *delta*. So the final position vectors of the current individual are calculated by:

X1−→=Xα−→−A1−→·(Dα−→)X1→=Xα→−A1→·(Dα→) (8)

X2−→=Xβ−→−A2−→·(Dβ−→)X2→=Xβ→−A2→·(Dβ→) (9)

X3−→=Xδ−→−A3−→·(Dδ−→)X3→=Xδ→−A3→·(Dδ→) (10)

X→(t+1)=X1−→+X2−→+X3−→3X→(t+1)=X1→+X2→+X3→3 (11)

where, A1−→A1→, A2−→A2→, A3−→A3→ are randomly generated vectors, and *t* represents the number of iterations.

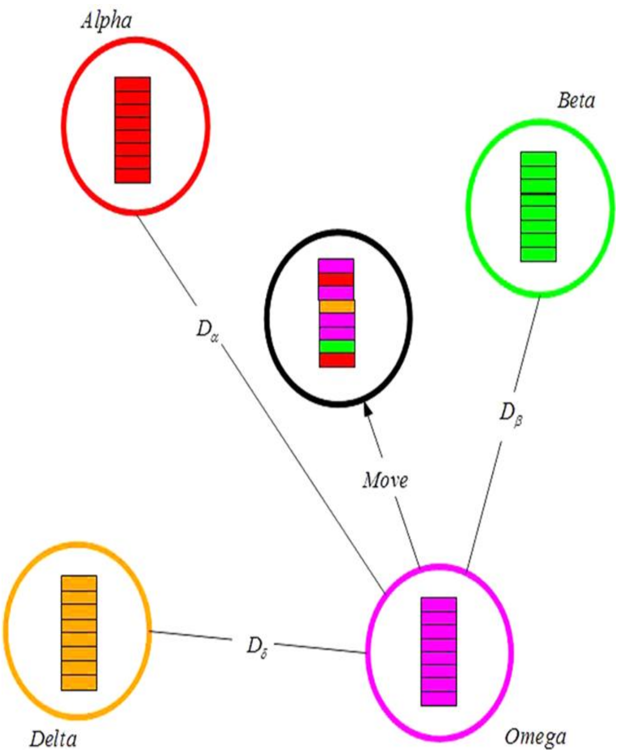



**Figure 1**

**The GWO Algorithm**

- Initialize the grey wolf population Xi (i = 1, 2, ..., n)
- Initialize a, A, and C
- Calculate the fitness of each search agent
- $X_\alpha$ =the best search agent
- $X_\beta$ =the second best search agent
- $X_\delta$ =the third best search agent

To see how GWO is theoretically able to solve optimization problems, some points may be noted:

- The proposed social hierarchy assists GWO to save the best solutions obtained so far over the course of iteration
- The proposed encircling mechanism defines a circle-shaped neighbourhood around the solutions which can be extended to higher dimensions as a hyper-sphere
- The random parameters A and C assist candidate solutions to have hyper-spheres with different random radii
- The proposed hunting method allows candidate solutions to locate the probable position of the prey
- Exploration and exploitation are guaranteed by the adaptive values of a and A
- The adaptive values of parameters a and A allow GWO to smoothly transition between exploration and exploitation
- With decreasing A, half of the iterations are devoted to exploration (|A|≥1) and the other half are dedicated to exploitation (|A|<1)
- The GWO has only two main parameters to be adjusted (a and C)

## 3. Application

The GWO algorithm was employed as a training algorithm for Multi-layer perceptron (Feedforward Neural Networks) in 2015 [3].

An improved grey wolf optimizer for training q-Gaussian Radial Basis Functional-link nets was proposed by Muangkote [4]. The grey wolf optimizer was utilized for solving economic dispatch problems as well [5]. An Application of Grey Wolf Optimizer for Solving Combined Economic Emission Dispatch Problems was done by Song et al. as well [6].

Feature Subset Selection Approach by Gray-Wolf Optimization was done by Emary et al. [7]

The GWO algorithm was used for optimum allocation of STATCOM devices on power system grid to minimized load buses voltage deviations and system power losses [8].

An improved version of GWO using evolutionary population dynamics was also proposed recently [9].

The GWO algorithm was utilzed to optimizing key values in the cryptography algorithms.[10].

## 4. Conclusion

This Literature paper is to introduce the grey wolf optimization (GWO) algorithm to the electromagnetics and



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antenna community. GWO is a metaheuristic algorithm inspired by the leadership hierarchy and hunting mechanism of grey wolves.. GWO has been applied to solve practical optimization problems in engineering [25] such as tension/compression spring design, welded beam design, pressure vessel design, and optical buffer design. GWO has also been used in areas like allocation of static synchronous compensator (STATCOM) devices on power system grid [26] and to solve economic dispatch problems [27, 28] and so forth. In [29], an improved grey wolf optimizer for training q-Gaussian Radial Basis Functional-link nets was proposed.

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