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A Large Scale Analysis of Grey Wolf Optimization Techniques: Recent Trend

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***Abstract*— This paper provides a detailed overview of the Grey Wolf Optimizer (GWO).The social hunting behaviour of grey wolves served as the inspiration for the recently introduced meta-heuristic known as the GWO algorithm. The GWO has been employed in almost all optimization areas and engineering practice and it has grown more and more important as a tool of swarm intelligence. The GWO algorithm and its variations have successfully shed light on several difficulties from various fields. The original GWO algorithm needed to be altered or hybridized in order to be used to reveal various challenges. This paper undertakes a thorough analysis of this active and developing field of swarm intelligence in order to demonstrate how the GWO algorithm may be related to every problem that arises in practice. However, it enables less experienced researchers and algorithm makers to use this simple but incredibly powerful method for problem solving. It frequently makes sure that the results obtained will live up to expectations.**

***Index Terms*— Optimization, Swarm Intelligence, Natured inspired Algorithm, Grey Wolf Algorithm**

I. INTRODUCTION

The concept of Meta heuristic techniques based in variety of application in the field of engineering basically this method depends on basic concept and execution is simple, need not require gradient information, also bypass to local optima and used in large range of problems covering different field [1-5]. The majority of real-world optimization problems are remarkably nonlinear and multimodal, and meta-heuristic algorithms have shown promise in their ability to solve these problems. Every metaheuristic algorithm makes use of a clear trade-off between local search and randomization [6]. These algorithms can investigate the best solutions for challenging optimization problems, however finding the best answers is not guaranteed. For global optimization, meta-heuristic techniques might be suitable [7].
Meta-heuristic algorithms that draw inspiration from nature address optimization problems by modeling natural phenomena [6].That can be divided in to three categories.1.Swarm intelligence (SI), II.Evolutionary Algorithm (EA) and III. Physical based algorithm.
Swarm intelligence mimic the sophisticated social behavior of animal groupings. In general, evolutionary algorithms abandon such data from generation to generation while Swarm Intelligence-based algorithms capture and utilize all knowledge about the search space as the algorithm advances. The examples of representative algorithms in Sis are Particle Swarm Optimization (PSO) [14], Ant Colony Optimization (ACO) [15], Firefly

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Algorithm (FA) [16], Bat Algorithm (BA) [17], and Artificial Bee Colony algorithm (ABC) [18].
Evolutionary Algorithm imitate the animal behavior that evolved over time in the natural world. The search algorithms start with generated answers that are random, commonly referred to as the population, and they continue to develop through subsequent generations. The key benefit of Evolutionary Algorithm is that the best individuals have combined to create new generations, which improves population performance over the course of iterations [8]. Genetic algorithms (GA) [9], Genetic Programming (GP) [10], Evolution Strategy (ES) [11], Differential Evolution (DE) [12], and Biogeography-Based Optimizer (BBO) [13] are a few of the well-known evolutionary-based tactics.
Based upon physical law of the universe, physical based algorithm has been used. The Gravitational Search Algorithm (GSA) [23], Multi-verse Optimizer (MVO) [24], Magnetic Optimization Algorithm (MOA) [25], Electromagnetic Field Optimization (EFO) [26], and Charged System Search (CSS) [27] are the example of physical based algorithm.
Grey wolf optimization (GWO) [28], a capable and recently developed meta-heuristic evolutionary optimization approach, was introduced by Mirjalili et al. in 2014. It is based on the social hierarchy and hunting behavior of grey wolves. The grey wolf (Canis lupus), a member of the Canidae family, served as the model for the GWO technique. Grey wolves live in packs, which range in size from 5 to 12. The pioneer is referred to as the alpha and is competent of make decisions regarding hunting, sleeping arrangements, etc. The second, known as beta, supports the alpha in making decisions. The alpha wolf must be revered by the beta wolf. From a rank perspective, omega is the lowest grey wolf, and it shares data with all other prevailing wolves. The other grey wolves have given the omega and delta their names. Exploration and exploitation are the fundamental subcategories of metaheuristic algorithms [29, 30]. Exploration ensures that the algorithm will reach unique promising locations inside the search space, whilst exploitation ensures that the programme will look for the best solutions in the designated area [31].

II. GWO ALGORITHM GENERAL STRUCTURE

These algorithm contain the strict social structure in their population, which may be divided into four layers [28] such as α (Alpha) , β (Beta), δ (Delta) and ω (Omega). This social structure is essential to the hunting process. α referred as leader who leads for hunting process. According to the team model of hunting, wolves look for, track, chase, and approach their prey. The victim is then pursued, surrounded, and harassed until it stops moving. When the enclosure is sufficiently small, the wolves β and δ who are closest to the prey begin attacking, and the other wolves act as reinforcements. Supplements adjust the encirclement when a prey breaks loose dependent on the prey's location. This enables a continuous attack on the target, leading to the prey's capture.

Fig 1 Population structure of grey wolves

The first, second, and third-best search agents in the GWO algorithm are designated as α,β and δ, respectively. Prey's position with relation to the overall best solution to the optimization challenge. The GWO algorithm's optimization procedure is as follows. In a search space, it starts by randomly creating a number of grey wolves. The position of the prey is determined throughout the course of repetitions by α, β and δ other wolves update their positions based on α, β and δ positions. The hunt then ends with an attack on the target after it stops moving after being circled and approached. The GWO method contains various comparing definitions that are defined as follows [28]. The three wolves should have more knowledge of the likely location of prey in order to mimic the group hunting behavior of grey wolves. They determine where the prey is in the search area, and the wolves then set up camp around the prey at random. In order to update the positions of the wolves in accordance with the best three positions.

Separation between the grey wolf and its prey

$$S = \left|\vec{C}.\overrightarrow{X_p}\,(t) - \overrightarrow{X_g}\,(t)\right| \qquad (1)$$

The current iteration t, X_g and X_p are the position of grey wolf and prey.
C is the coefficient vector and is determined by

$$\overrightarrow{C} = 2\overrightarrow{r_1} \qquad (2).$$

The value of $\overrightarrow{r_1}$ lies between [0, 1]
The location of prey is

$$\vec{X}\,(t+1) = \vec{X}_p\,(t) - \vec{A}\,\overrightarrow{D} \qquad (3)$$

Where A is coefficient vector

$$\vec{A} = 2.\vec{d}.\vec{r}_2 - \vec{d} \qquad (4)$$

The value of d is linearly decreased from 2 to 0 in entire iteration process.
The position of grey wolf is updated based on the following equation.

$$\{\vec{S}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| \qquad (5)$$

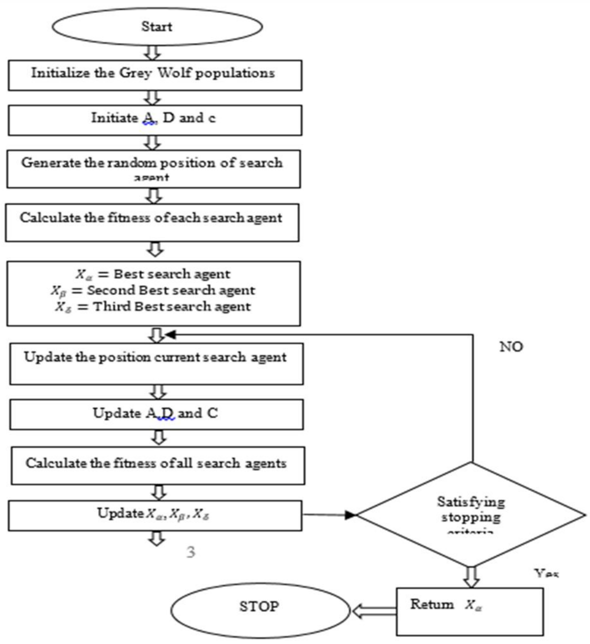
$$\{\vec{S}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| \qquad (6)$$

$$\{\vec{S}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \qquad (7)$$

The separation between the search agent is calculated by using equation (5), (6) and (7).

III. GWO STRUCTURE

A. FLOW CHAT



B. Algorithm

- ❖ The population of grey wolf is optimized by using X_i (i= 1,2,3,…….n)
- ❖ Define d, A and C
- ❖ Determine the position of search agent

  where X_α = Best search agent

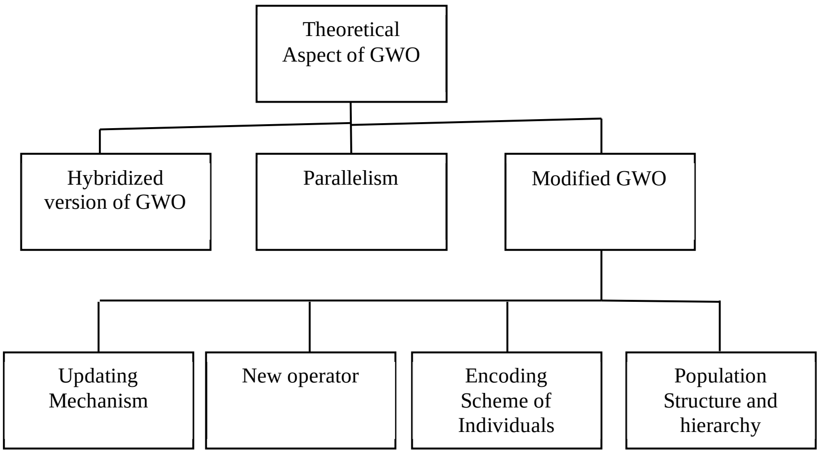
X_β = Second Best search agent

X_δ = Third Best search agent

❖ While (t < max iteration)
For Each Search agent
By using the equation $\vec{X}(t+1) = \vec{X}_1 + \frac{\vec{X}_2}{2} + \frac{\vec{X}_3}{3}$, update the position of current search agent.
End
Update A,D and C
Update the value of $\vec{X}_\alpha$, $\vec{X}_\beta$, $\vec{X}_\delta$
End.

IV. GWO ALGORITHM'S TAXONOMY

The mathematical model of the GWO algorithm is presented briefly in this section.



A. Hybridized version of GWO

In general, hybridization in the context of metaheuristics refers to integrating two or more algorithms in order to harness the advantages and powerful aspects of each. GWO has been hybridized with various metaheuristic algorithms in the literature. In [33] Kamboj explain a sequential hybridization of GWO and PSO for optimizing a single-area unit commitment problem. The quality of the generated solutions in Neural Computing and Applications was competitive; but, due to the long sequential execution time, this approach suffers from slower convergence. Other studies, such as [32], recommended combining GWO with DE. When compared to PSO and DE, both efforts produced extremely competitive outcomes.

B. Parallelism

Parallelism is a method that can be used effectively in population-based metaheuristics in which the population is separated and divided into a number of subpopulations, each of which can be evolved on a distinct machine processor. Parallelism can significantly shorten the optimizer's execution time while also improving solution quality. In [34], a parallel version of GWO was implemented. In this implementation, subgroups evolve independently and trade the best members after a predetermined number of rounds. A comparison with the original GWO reveals that parallelism greatly improves performance in terms of solution quality and running speed time across four separate benchmark functions.

C. Modified GWO

The modified form of GWO is categories in to following parts:
- ✓ Updating Mechanism
- ✓ New operator
- ✓ Encoding Scheme of Individuals
- ✓ Population Structure and hierarchy.

D. Updating Mechanism

The author of [35] investigated the idea of improving the exploration process in GWO by decreasing the value of a using an exponential decay function, as shown in equation 8. By using different benchmark function, they compared by taking different algorithm PSO,BAT,CS and GWO.Finally they observed that modified version

$$a = 2(1 - \frac{i^2}{max_i{}^2}) \quad (8)$$

Where i denote Current iteration and max $_i$ denote maximum iteration.
Rodriguez et al. offered three different strategies for updating the placements of the omega wolves in the algorithm in [35]. The weighted average is one of the three approaches. Based on fitness and fuzzy logic. Although the performance of each method varies depending on the situation, they claimed that the fuzzy logic-based strategy performed better in the majority of the examined benchmark functions.

E. New Operators

The following are the primary works in this field of study.
In an attempt to boost population variety in GWO, the authors proposed in [36] a modified version of the GWO that contains a simple crossover operator between two randomly distinct individuals. The crossover operator's goal is to make it easier for pack members to share information. A comparison of GWO and its modified version based on six benchmark functions revealed that the crossover operator improved GWO solution quality and convergence speed. Later, Chandr et al. [7] used this version of GWO to identify web services with optimal quality-of-service criteria.
Saremi et al. [37] examined improving GWO with another sort of operator known as evolutionary population dynamics (EPD). EPD was used in GWO to eliminate the worst individuals in the population and reposition them around the population's leading wolves, i.e. a, b, and d. According to the authors, using this operator enhances the median of the population throughout the course of iterations and has a favorable influence on the exploration and exploitation processes.
Zhang and Zhou [39] created PGWO by incorporating the Powell optimisation algorithm into GWO as a local search operator. Powell's algorithm is a method for determining the minimum of a function that does not need to be differentiable and does not take derivatives. The algorithm searches in a bidirectional fashion along search vectors [38].
Zhou et al. [40] proposed integrating GWO with chaotic local search to tune the parameters of the equivalent model of a small hydro generating cluster. When compared to PSO, their version of GWO performed noticeably better.

F. Encoding Scheme of Individuals

In [41] proposed a modification to GWO at the individual encoding scheme. Instead of the more common real-valued encoding method, the authors chose a complex-valued one. The genes in the person have two major parts in this encoding: an imaginary part and a real part.

G. Population Structure and Hierarchy

GWO has a distinct hierarchical population structure. Four different types of individual each type has just one person, and the others are the fourth type. This notable structure has prompted several scholars to investigate the impact of making some changes to the hierarchy. Yang et al. [42] published an important paper in which they proposed a variation of GWO with a modified leadership structure. The variant's population is separated into two autonomous subpopulations: the first is called the cooperative hunting group, and the second is called the random scout group. The scout group's task is to conduct a wide exploration process, whereas the cooperative hunting group's task is to conduct a deep exploitation.
This variant's inventors used it to tune the parameters of interactive proportional-integral controllers in doubly fed induction generator-based wind turbines. They compared their findings to those of GA, PSO, GWO, and MFO. When compared to the other optimizers, their findings exhibited superior fitness values and higher stability.

V. APPLICATION OF GWO

A. Challenges in Engineering Design

The enhancement of engineering processes holds significant importance within the field, directly impacting the quality of life. The versatility of Grey Wolf Optimization has led to its adoption in addressing various engineering challenges, a topic thoroughly explored in this section

For Design and Control

The algorithm's performance was assessed and validated through a comparative analysis with well-known algorithms [43]. The results demonstrated that GWO outperformed other renowned heuristic algorithms examined in the study. Additionally, in [44], the authors applied the algorithm to address engineering design challenges, illustrating its applicability to the design of optical instruments.

Scheduling

In their work [45], Lu et al. introduced a multi-objective discrete grey wolf optimizer (MODGWO) to address a practical scheduling problem in welding production. The effectiveness of MODGWO was assessed by comparing it with NSGA-II and SPEA2 across various instances. Results revealed that MODGWO outperformed both NSGA-II and SPEA2. Similarly, Panwara et al. [46] applied the Binary Grey Wolf Optimizer (BGWO) to determine the dedication timetable for the UC problem. Experimental results demonstrated the superior performance of BGWO in solving UC problems for small, medium, and large-scale systems compared to other approaches considered in the study.

Path Planning and Robotics

In their study [47], Zhang et al. applied Grey Wolf Optimization (GWO) to address the two-dimensional path planning problem for Unmanned Combat Aerial Vehicles (UCAV). GWO demonstrated highly competitive performance when compared to alternative techniques, showcasing effectiveness comparable to that of advanced algorithms. Additionally, Jain et al. [42] devised a hybrid system integrating Particle Swarm Optimization (PSO) and GWO to tackle the problem of robotic localization.

B. Machine Learning

GWO has been utilized in various machine learning tasks [48--50], which will be elaborated upon in the subsequent discussion

Optimization Problem

Mirjalili et al. [48] employed the multi-objective grey wolf optimizer (MOGWO) to address a multi-criterion optimization problem. Experimental results demonstrated the favorable performance of the MOGWO algorithm, surpassing MOEA/D and MOPSO.

Clustring:

Jeet [49] employed the MOGWGA algorithm to cluster a set of five sample software, considering six clustering objectives for the application. The algorithm's performance was evaluated against Two-Archive, MOGA, and NSGA-II based methods. The results indicate that the MOGWGA algorithm surpasses the other two approaches in addressing the problem discussed in the paper.

Feature Selection:

Singh et al. [50] employed the Multi-objective Grey Wolf Optimizer (MOGWO) to navigate the feature space, aiming to identify the optimal subset that effectively describes data with minimal redundancy while maintaining high classification accuracy. The proposed method was compared against PSO and GA, as well as other optimization problems aimed at finding optimal solutions for specific challenges. Notably, MOGWO outperformed both PSO and GA in these evaluations.

VI. CONCLUSION

This study offers a comprehensive overview of Grey Wolf Optimization (GWO) applications across various fields, intending to provide researchers and engineers with accessible insights into its practical use. The aim is to inspire researchers to develop new GWO variants that address existing algorithmic shortcomings. Grey Wolf Optimization can be broadly categorized into single-objective GWO and multi-objective GWO. The former focuses on solving single-objective problems, while the latter is tailored for addressing multiple objective problems. The review underscores that GWO algorithms have gained attention across diverse domains, including classical engineering design problems, image processing, clustering, job scheduling, Insights drawn from GWO applications suggest that it outperforms existing bio-inspired algorithms like BA, GA, FA, PSO, and others in terms of performance. However, the study also notes that the applications of GWO are relatively limited in the literature due to its novelty, with ongoing exploration by the research community.

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