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Medical Disease Prediction with Grey Wolf Optimizer Using Levy and Gaussian Random Walk Distributions

[1]Kamala Srinidhi.V, [2]Sheeba Betsy, [3]Alamelu.T, [4]S.Kanmani

[1,2,3]B.Tech Students, [4]Professor, Department of Information Technology,
Pondicherry Engineering College, Puducherry, India
[1]kamalasrinidhiv99@gmail.com, [4]kanmani@pec.edu

Abstract: This paper proposes an enhancement of the optimization algorithm called Grey Wolf optimizer (GWO) [1] using various random walk distributions. GWO algorithm is used for the relevant attributes selection process. This helps in improving the efficiency of the medical disease prediction system. GWO algorithm recognizes the different related attributes such as breast cancer, heart related disease, diabetes and etc. It also, employs minimum parameters such as blood pressure, cholesterol, and etc. GWO, which is nature, bio-inspired algorithm that logically divides search process into two categories: Exploration and Exploitation. The proposed idea is to enhance the exploration characteristics of the algorithm. This can be achieved by incorporating Levy or Gaussian distribution along with Random Walk (RW) in Grey Wolf Optimization Algorithm (GWO) [4] instead of Cauchy Distribution that fully concentrated on maximizing exploitation, which is proven by the outperformance of the algorithm in all seven unimodal benchmark functions.

Keywords: CEC2014, Grey Wolf Optimizer, Random Walk.

1. INTRODUCTION

Grey Wolf Optimizer (GWO) Algorithm is a swarm intelligence algorithm .It is used in Solving the problems of continuous optimization as well as real world optimization. The paper involves two important aspects- the ability of a modified algorithm by grey wolf primarily to enhance the hunt. The stochastic process which was enabled by RW-GWO was anticipated. Secondly, its success is seen against that of RWGWO with numerous stochastic process distributions on IEEE CEC 2014[5] benchmark issues. Grey Wolf Optiizer is the algorithm in the swam intelligence group that is based on hierarchy of leadership. Grey wolves which is also known as western or timber wolves always live in a pack of approximately 5–11 wolves.

The concept of The key characteristic of wolf's pack is social hierarchy. They categorize their party into four groups of wolves to hunt the prey and to maintain the discipline within pack. The key characteristic of wolf's pack is social hierarchy. They categorize their party into four groups of wolves to hunt the prey and to maintain the discipline within pack. Second type wolves are the submissive wolves. They are liable to transmit the alpha wolf signals to the other wolves and help the alpha wolf make decisions such as hunting and choosing residence place etc. Wolves are called beta wolves (β), in this group. The wolves which have permission to consume food at the end are included in the last group of the pack.

The quest method includes three phases – I run after and hit the prey. (ii) skirting the prey and (iii) assaultive the prey. Mathematically speaking, with the aid of these leading wolves each wolf updates its place in GWO. Thus α, β and δ Wolves region join leading accountable search agents in changing each wolf's condition to providing optimal guidance to the prey. It is therefore critical that these leading wolves should be the most efficient in every iteration, so that every wolf can get an optimal steering to approach a prey.

2. LITERATURE SURVEY

GWO is a nature-inspired algorithms logically divide the search process into two tendencies: Exploration and Exploitation. The wolves' encircling strategy around the prey is modelled mathematically by proposing the following equations such as:

$$X_{t+1} = X_{p,t} - \mu . d \quad (1)$$

$$d = |c. X_{p,t} - X_t| \quad (2)$$

$$\mu = 2. b. r_1 - b \quad (3)$$

$$c = 2. r_2 \quad (4)$$

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Where X_{t+1} Is the wolf's place at (t+1)th iteration X_t is The wolf's place at tth iteration, $X_{p,t}$ Is a prey's location at the tth iteration. d is the vector of difference represented by (2), μ and c Are coefficient vectors, and b is a linearly decreasing vector, expressed as 2 to 0 over iterations

$$b = 2-2.\left(\frac{t}{maximum\ no.\ of\ iterations}\right) \quad (5)$$

and r_1, r_2 Are the random vectors uniformly distributed whose variable is between 0 and 1. The grey wolves' hunting strategy is also mathematically modelled by approximating the prey location with the aid of α, β and δ solutions (wolves). Hence every wolf can change their positions by following this approximation by:

$$X' = X_\alpha - \mu_\alpha . d_\alpha \quad (6)$$

$$X' = X_\beta - \mu_\beta . d_\beta \quad (7)$$

$$X' = X_\delta - \mu_\delta . d_\delta \quad (8)$$

Where $X_\alpha, X_\beta, X_\delta$ are the positions approximated by α, β and δ solutions(wolves) with the help of eq.(1). It's clear that when the prey starts moving, the wolf will kill the prey and finish their hunting cycle during this way. When to go hunting or c > 1 Wolf will explore the entire prey (optima) quest space and wolves will explore the |μ|> 1 it the search space when |μ| < 1 or c < 1.When t → maximum number of iterations, then by eq. (5) b→0⇒μ→0 Therefore Coefficient c is responsible for exploration in this case. In this way, grey wolves complete their hunting cycle by repeating the steps of surrounding and hunting as mentioned above. Since it is defined in GWO algorithm that each of the pack's wolves will update their positions consistent with the pack's leading wolves with the aid of eq. (9). (18). But then there is the obvious problem

$$X_{t+1} = \frac{(X_1 + X_2 + X_3)}{3} \quad (9)$$

Arises what leading wolf helps to change alpha wolf's position, since it is that Modified by Wolves Chief. In the pack members, therefore, an improvisation is required to avoid the question of premature convergence due to the stagnation in local optima and to sustain a social behavior within the group. To accomplish this, it has been suggested within the present paper stochastic method based on Grey Wolf Optimizer during which leaders explore the search space via stochastic method then omega wolves update their role by following them.

3. PROPOSED WORK

Problem Definition

The proposed idea is to use Levy or Gaussian distributions instead of Cauchy distribution in Random Walk technique which is used to improve the efficiency of Grey Wolf Optimization algorithm to draw the step size. Like, Cauchy Distribution Levy and Gaussian also comes under stable distributions.

Levy Distribution will assist GWO in looking out supported deeper looking out patterns. This idea, it will be ensured that GWO will handle world looking out a lot of expeditiously. By this manner, the stagnation problem can also be relieved. In addition, the quality of the candidate solutions should be enhanced in Lévy embedded GWO[2] throughout the simulation.

Gaussian Distribution is one of the stable distributions with heavy-tail. This distribution is never used in the GWO algorithm earlier. Introducing Gaussian Distribution as an alternative for Cauchy Distribution in Random Walk technique is to improvise the exploration behavior which RW-GWO lagged behind. In RW-GWO the performance of exploitation, avoidance of local optima, avoiding stagnation problem are efficient.

The main objective is to compare the performance of the algorithm with different distributions such as Cauchy, Levy and Gaussian distributions. The best distribution among these is found to extract the optimal search ability. The performance is analyzed in comparison with GWO on 23 benchmark problems which are classical functions used by various other researchers. The proposed algorithm can also be used to solve real-life application[10][11] problems.

Pseudo code of the algorithm

The pseudo code for the proposed RW- GWO algorithm is listed in Figure.1.1

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```
Initialize the Grey wolf population x_i (i = 1,2,...,n)
Initialize parameters b,μ and c as defined in subsection 2.2.2
Initialize l = 1, the iteration number
Evaluate the fitness of each wolf
Select  α = fittest wolf of the pack
        β = second best wolf
        δ = third best wolf
while l < maximum number of iterations
 Evaluate the fitness of each wolf
        for each leader wolf
            find new position y_i of the leaders x_i by random walk
             if f(y_i) < f(x_i)
             update the leaders
        end
        for each ω wolf
          update the position by equation (9) and apply greedy approach between current and
        updated positions
        end
    update b,μ and c
    update α,β and δ wolves
    l = l + 1
end
```

Figure 1.1 Pseudo code of RWGWO

Architecture Diagram

The proposed work has been divided into the following modules.

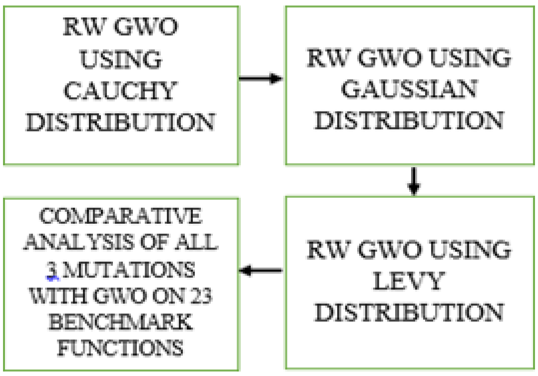

Figure 1.2. Architecture Diagram

Module Description

Implementation of existing RW-GWO algorithm (Cauchy Distribution)

As the GWO begins with a population of initial wolves say x_i ;i =1, 2,. ., n; Consequently, iteratively a random walk has been introduced in each iteration for only the α, β and π members of the population in which the αi parameter has been taken as the vector that is proceeding. This algorithm integrates random walk, in which step size is extracted from a Cauchy distribution. The implementation is on 23 well known classical benchmark functions out of which 7 are unimodal benchmark functions used for evaluation of exploitation characteristics of the algorithms, 6 are multimodal benchmark functions and remaining 10 are fixed dimension multimodal benchmark functions for evaluation of exploration characteristics of the algorithms.

Motivation Behind Using Cauchy Distribution The explanation for considering Cauchy's distributed random phase size is that because the variance of a Cauchy distribution is infinite, it may take often a longer leap which is quite successful at the time of stagnation and thus very helpful for the Cauchy distribution Leading wolves to discover the prey-finding area and provide a great guide to other wolves. So, in both algorithms the function evaluation remains the same.

Implementation of RW-GWO using Levy Distribution in order to boost the efficacy of GWO, Lévy distribution[3] and greedy selection strategies are integrated with the modified hunting phases. LF is a class of scale-free walks with randomly-oriented steps according to the Lévy distribution.[8] For this purpose, two main modifications are proposed:

1) The Levy Distribution concept is embedded into GWO.

2) The greedy selection (GS) strategy is employed for LF-based GWO. The implementation is on 23 well known classical benchmark functions out of which 7 are unimodal benchmark functions used for evaluation of exploitation characteristics of the algorithms, 6 are multimodal benchmark functions and remaining 10 are fixed dimension multimodal benchmark functions for evaluation of exploration characteristics of the algorithms.

Motivation Behind Using Levy Distribution The Levy Distribution [14] can assist GWO in searching based on deeper searching patterns. This idea, it will be ensured that GWO will handle world looking out a lot of expeditiously. By this manner, the stagnation problem can also be relieved. In addition, the quality of the candidate solutions should be enhanced in Lévy embedded GWO throughout the simulation.

Implementation of RW-GWO using Gaussian Distribution The Gaussian Distribution is used in the GWO algorithm using Random Walk technique to calculate the step size of the walk.[13] The Gaussian distribution is additionally normally referred to as the "normal distribution" and is sometimes represented as a "bell- shaped curve". The implementation is on 23 well known classical benchmark functions out of which 7 are unimodal benchmark functions used for evaluation of exploitation characteristics of the algorithms, 6 are multimodal benchmark functions and remaining 10 are fixed dimension multimodal benchmark functions for evaluation of exploration characteristics of the algorithms.

Motivation Behind Using Gaussian Distribution Gaussian Distribution is one of the stable distributions with

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heavy-tail. This distribution is never used in the GWO algorithm earlier. Introducing Gaussian Distribution as an alternative for Cauchy Distribution in Random Walk technique is to improvise the exploitation behavior which RW-GWO lagged behind. In RW-GWO the performance of exploration, avoidance of local optima, avoiding stagnation problem are efficient. Comparative Study with the existing GWO algorithm The ultimate goal of the proposed work is to explore the best distribution in terms of Random Walk technique in GWO to extract the maximum efficiency in terms of both exploration and exploitation. Thus, the three alternative distributions Cauchy, Levy and Gaussian distribution are applied on Random Walk technique incorporated in GWO one by one and the results are obtained. The results are to be compared in terms convergence curve and the best solution obtained so far in 1000 iterations the efficiency of the algorithm in balancing th exploration and exploitation properties. The final goal is to conclude the best alternative amongst the three distributions that can be incorporated with RW- GWO to extract its maximum potential. The distribution which is suitable to solve real-life application problem[7][9] is also determined.

4. RESULT ANALYSIS

The performance of the three algorithms RW GWO using Cauchy, Gaussian and Levy distributions are compared with the existing GWO algorithm on 23 standard classical benchmark functions implemented by many other authors for evaluation as it consists of both unimodal (F1-7) benchmark functions, multimodal (F8-13) benchmark functions and fixed dimension multimodal(F14-23) benchmark functions. As it is proven that evaluation of an algorithm against unimodal functions show the efficiency of exploitation property and multimodal functions show the efficiency of exploration property, they are used here for performance analysis.[6]

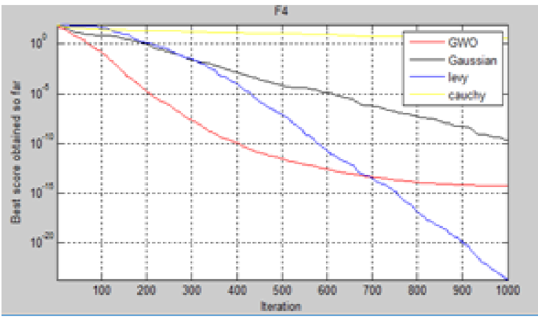

Figure 1.3. Convergence curve for F4 Unimodal bench mark functions

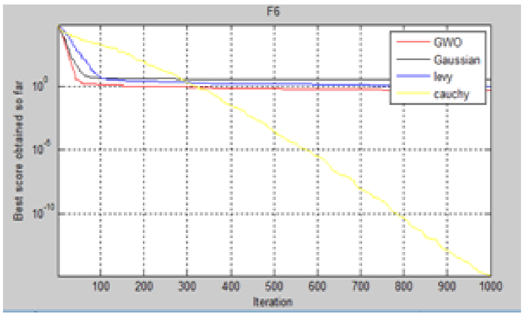

Figure 1.4. Convergence curve for F6 Unimodal Benchmark functions

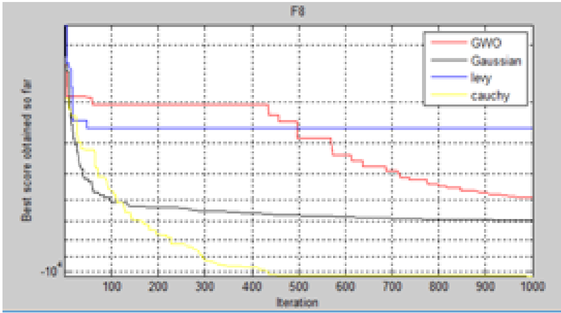

Figure 1.5. Convergence curve for F8 Multimodal functions

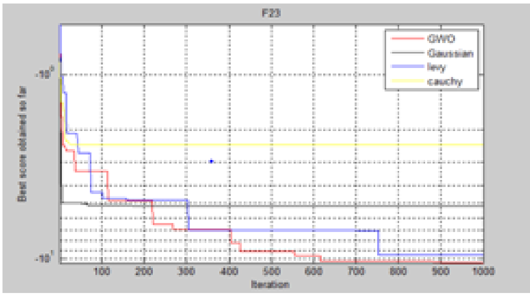

Figure 1.6 Convergence curve for F23 Multimodal function

Table 1. Properties of unimodal benchmark functions

NO	FORMULA NAME	CONTINUITY	DIFFRENTIABILITY	SEPARABILITY	SCALABILITY	BEST PERFORMANCE
F1	SPHERE FUNCTION	Continuous	Non-Differentiable	Separable	Scalable	Cauchy
F2	SCHWEFEL 2.22 FUNCTION	Continuous	Differentiable	Non-Separable	Scalable	Cauchy
F3	SCHWEFEL 1.2 FUNCTION	Continuous	Differentiable	Non-Separable	Scalable	Cauchy
F4	SCHWEFEL 2.21 FUNCTION	Continuous	Non-Differentiable	Non-Separable	Scalable	Cauchy
F5	ROSENBROCK FUNCTION	Continuous	Differentiable	Non-Separable	Scalable	Cauchy
F6	STEP 2 FUNCTION	Discontinuous	Non-Differentiable	Separable	Scalable	GWO
F7	QUARTIC FUNCTION	Continuous	Differentiable	Separable	Scalable	Cauchy

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Table.1.2: Properties of multimodal benchmark functions

NO	FORMULA NAME	CONTINUITY	DIFFRENTIABILITY	SEPARABILITY	SCALABILITY	BEST PERFORMANCE
F8	SCHWEFEL 2.26 FUNCTION	Continuous	Non-Differentiable	Separable	Scalable	Levy
F9	RASTRIGIN FUNCTION	Continuous	Differentiable	Separable	Scalable	Gaussian
F10	ACKLEY'S 1 FUNCTION	Continuous	Differentiable	Non-Separable	Scalable	Cauchy
F11	GRIEWANK'S FUNCTION	Continuous	Differentiable	Non-Separable	Scalable	Gaussian
F12	PENALIZED 1 FUNCTION	Discontinuous	Differentiable	Non-Separable	Non-Scalable	Gaussian
F13	PENALIZED 2 FUNCTION	Discontinuous	Differentiable	Non-Separable	Non-Scalable	Gaussian
F14	DE JONG'S FUNCTION	Continuous	Differentiable	Separable	Non-Scalable	Gaussian

Table 1.3. Properties of multimodal benchmark functions

NO	FORMULA NAME	CONTINUITY	DIFFRENTIABILITY	SEPARABILITY	SCALABILITY	BEST PERFORMANCE
F15	XIN-SHE YANG N.3 FUNCTION	Discontinuous	Differentiable	Separable	Scalable	Levy
F16	XIN-SHE YANG N.4 FUNCTION	Discontinuous	Non-Differentiable	Non-Separable	Scalable	NO
F17	BRANIN RCOS FUNCTION	Continuous	Differentiable	Non-Separable	Non-Scalable	NO
F18	GOLDSTEIN PRICE FUNCTION	Continuous	Differentiable	Non-Separable	Non-Scalable	NO
F19	HARTMAN 3 FUNCTION	Continuous	Differentiable	Non-Separable	Non-Scalable	Cauchy
F20	HARTMAN 6 FUNCTION	Continuous	Differentiable	Non-Separable	Non-Scalable	Levy

The overall analysis shows that on the total number of 23 bench mark functions there is no improvement made by any of the proposed algorithms in three multimodal benchmark functions (F16-18). In 10 (F1- 5, F7, F10, F19, F21, F23) out of the 20 remaining benchmark functions RW GWO (Cauchy distribution) algorithm outperformed out of which Table 1.1: Properties of unimodal benchmark functions property is highly efficient and four are multimodal functions.

The Gaussian distribution used RW GWO algorithm, it outperformed in 5 benchmark functions (F9, F11-14) out of which all the 5 are multimodal benchmark functions proving its efficiency in exploration property in comparison with the other algorithms.

The Levy distribution used RW GWO, it outperformed in 4 benchmark functions out of which all are multimodal benchmark functions (F8, F15, F20, F22) proving its efficiency in exploration property in comparison with the other algorithms.

The GWO outperformed only 1 unimodal benchmark function (F6) which shows that its efficiency is not appreciable in comparison with its mutants in terms of exploration, exploitation, local maxima avoidance and stagnation.

For Cauchy distribution, It tends to be continuous in 8 benchmark functions, differentiable in 6 and non-differentiable in 2 benchmark functions, separable in 2 and non-separable in 6 benchmark functions and it is scalable in 7 and non-scalable in 1 benchmark functions out of 8 .

For Levy Distribution, It tends to be continuous in 2 and discontinuous in 1 benchmark functions, differentiable in 2 and non-differentiable in 1 benchmark functions, separable in 2 and non- separable in 1 benchmark functions and it is scalable in 2 and non-scalable in 1 benchmark functions out of 3.

For Gaussian distribution, It tends to be continuous in 3 and discontinuous in 2 benchmark functions, differentiable in 5 benchmark functions, separable in 2 and non- separable in 3 benchmark functions and it is scalable in 2 and non-scalable in 3 benchmark functions out of 4.

For GWO, It tends to be discontinuous in 1 benchmark function, non-differentiable in 1 benchmark function, separable in 1 benchmark function and it is scalable in 1 1 benchmark function out of 1.

5. CONCLUSION

In medical field, many researchers focused only on prediction of various disease using different medical applications. These reasons behind using GWO was most of the swarm intelligent methods are usually used to solve the optimization problem which doesn't have the leader to monitor the entire proceeding period. This drawback was resolved in GWO method since the grey wolves have individual leadership capacity. This GWO algorithm [16] recognizes the different related attributes such as breast cancer, heart related disease, diabetes and etc. It also, employs minimum parameters such as blood pressure, cholesterol, and etc. cholesterol and etc. Also the algorithm selects the relevant disease and their related attributes. The process of feature selection method[17] consists of 4 major steps: (1) generation: generate the candidate subset; (2) evaluation: evaluate the subset; (3) stopping criterion: decide when to stop;(4) validation: check whether the subset is valid. Based on whether the evaluation step includes a learning algorithm or not, the feature selection methods can be classified into two categories: filter approaches and wrapper approaches.

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Filter approaches are independent of any learning algorithm and sometimes computationally less costly and more general than wrapper approaches, while wrapper approaches evaluate the feature subsets with a learning algorithm and typically produce better results than filter approaches for particular problems. In diagnosis scenario, high diagnostic performance is usually preferred, even a small lift in accuracy can make significant difference. Therefore, the wrapper approach is adopted to get the higher classification performance. Generally, metaheuristics are commonly used for locating the optimal feature subset in wrapper approaches. In future, research work can be extended as an efficient hybrid technique for improving the efficiency of different medical disease classification. Grey Wolf Optimizer has been experimented with different distributions such as Cauchy, Gaussian and Levy distribution implemented in Random Walk technique. GWO is based on leadership hierarchy and hunting behaviour of grey wolves. The existing RW GWO with Cauchy distribution is efficient in terms of exploitation characteristics. The RW GWO with Gaussian distribution is efficient in terms of exploration property. The performance and improvement have been analysed by best solution obtained in 1000 iterations in comparison with other alternatives.

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