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A Novel Hybrid Multi-Population GWO-BWO Method for IIR Filter Parameter Estimation

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Abstract
This study presents a novel evolutionary optimization technique known as the hybrid multi-population evolutionary algorithm, which blends the Grey Wolf Optimizer (GWO) and Black Widow Optimization (BWO) methodologies. The method is driven by the drawbacks of single-population algorithms, namely their inability to handle local optima and premature convergence. The suggested hybrid algorithm improves convergence performance by fusing BWO's fierce local search and cannibalism technique with GWO's global exploration capacity. The approach's Mean Square Error (MSE), convergence speed, and robustness are assessed while being tested against benchmark IIR filters. Experimental findings validate the superiority of the hybrid GWO-BWO technique when compared to Flower Pollination Algorithm (FPA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA).
Keywords: *System identification, Adaptive filtering, Flower pollination algorithm, Genetic algorithm, Particle swarm opti mization, Grey Wolf Optimizer (GWO) and Black Widow Optimization*

1. OVERVIEW

Basic methods in digital signal processing, communication systems, and control engineering include adaptive filtering [1] and system identification [2]. Finite Impulse Response (FIR) filters are still widely used because of their intrinsic stability and linear-phase characteristics, even though Infinite Impulse Response (IIR) filters are typically more computationally efficient and require fewer coefficients to obtain a given performance level [5]. Accurately predicting IIR filter settings is the primary challenge. Traditional methods, such gradient descent and the Least Mean Squares (LMS) algorithm, are prone to convergence toward local minima and frequently suffer from sensitivity to initialization. Researchers have looked into evolutionary computation techniques as a way to get around these issues. To enhance optimization performance in nonlinear and multimodal settings, algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have been developed. The Flower Pollination Algorithm (FPA) [6], a more contemporary method, has shown promise in locating unidentified IIR systems [3]. Expanding upon these developments, we suggest a hybrid multi-population Grey Wolf Optimizer–Black Widow Optimization (GWO-BWO) approach that blends the potent exploratory powers of GWO with the successful exploitation approach of BWO. The possibility of finding the global optimum is increased, population diversity is increased, and convergence is accelerated by this hybridization.

Evolutionary algorithms have been effectively used to solve a variety of engineering issues during the last 20 years, such as fractional-order differentiator design [9], digital filter design [7], system identification [6], and fractional delay filter design [8]. For system identification tasks, a large number of metaheuristics have been proposed, including GA [10], PSO [10], Gravitational Search Algorithm (GSA) [11], Cat Swarm Optimization (CSO) [12], Differential Evolution (DE) [13], Opposition-Based Bat Algorithm (OBA) [14], Firefly Algorithm (FA) [15], Cuckoo Search Algorithm (CSA) [16], and hybrid variants like PSO–GSA [17].

Rashedi et al. employing GSA to solve system identification problems [13], Chen and Luk developing digital IIR filters using PSO [10], and Yao and Sethares applying GA to parameter estimation for linear and nonlinear systems [6] are a few noteworthy contributions. While Karaboga employed DE to accomplish better adaptive IIR filter identification than GA [13], Panda et al. demonstrated that CSO performs better for IIR system identification than GA and PSO [12]. Additional developments include the OBA approach put forth by Saha et al. [14], the application of FA for filter coefficient optimization by Upadhyay et al., and the use of CSA for IIR system modeling by Patwardhan et al. [15]. By integrating PSO and GSA in a hybrid framework, Jiang et al. significantly improved performance [17].

Yang [18] presented the Flower Pollination Algorithm in 2012, which has demonstrated encouraging outcomes for IIR system identification and was inspired by biological processes. However, there is still room for development in terms of resilience, solution diversity, and convergence speed. These deficiencies are intended to be filled by the suggested GWO-BWO hybrid, which provides a more dependable and effective method of parameter estimation in adaptive filtering and system identification.

2. Identification of the IIR Filter System

An optimization problem may be used to represent the identification of an unknown IIR system:

$$y(k) + \sum_{i=1}^{N} a_i y(k-i) = \sum_{i=0}^{M} b_i u(k-i)$$

where $u(k)$and $y(k)$ are the filter input and output, respectively; N and M are the order of numerator and denominator, respectively. The filter parameters $\{a_i, b_i\}$ are adjusted to minimize the Mean Square Error (MSE) given input-output pairs:

$$J_{MSE} = E(e^2(k)) = \frac{1}{P}\sum_{i=1}^{P} (d(k) - y(k))^2$$

.For a given input signal u(k), the goal is to determine the parameter configuration that minimizes this error.

3. The Hybrid GWO-BWO Algorithm Under Proposal

3.1 Grey Wolf Optimizer (GWO):

One of the main responsibilities of control engineering is system identification, which involves using observed input-output data to create mathematical models that explain the behavior of dynamic systems. Reliable prediction, control, and problem diagnostics depend heavily on accurate parameter estimation. However, nonlinear dynamics, noisy measurements, or extremely complicated search landscapes frequently provide challenges for traditional identification techniques like gradient descent, recursive algorithms, and least squares estimates. Metaheuristic optimization techniques, especially those based on natural events, have shown themselves to be useful substitutes in certain situations.

The Gray Wolf Optimizer (GWO), first presented by Mirjalili et al. in 2014 [19], is among the most promising methods. The algorithm is based on the hierarchical social structure and cooperative hunting behavior of gray wolves in the wild. Potential solutions are depicted as wolves in this framework, and their locations are modified in accordance with the directives of the alpha, beta, delta, and omega wolves at the top of the hierarchy. Because of this hierarchy, GWO is able to strike a good balance between searching the entire space and utilizing the top potential answers.

By minimizing an objective function, usually the mean squared error (MSE) between actual system outputs and model-predicted responses, GWO is used to modify model parameters for system identification tasks. GWO is especially well-suited to complicated identification issues because of its adaptive search method, simple implementation, and capacity to avoid local minima [20]. In a variety of applications, such as linear and nonlinear system modeling, IIR filter parameter estimation, control design, and electrical system identification, comparative studies have demonstrated that GWO frequently performs better than traditional evolutionary algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE) [21][22].

In conclusion, the Gray Wolf Optimizer provides a reliable and effective method for estimating parameters in system identification, especially in difficult situations involving high-dimensional parameter spaces, noise, and nonlinearities.

3.2 Black Widow Optimization (BWO):

Researchers are increasingly using metaheuristic approaches, which draw inspiration from biological and evolutionary events, to address the difficulties presented by traditional identification methods. A relatively new yet intriguing method among them is the Black Widow Optimization (BWO) algorithm, which was put up by Hayyolalam and Kazem in 2020 [23]. The algorithm incorporates processes including reproduction, offspring creation, cannibalism, and mutation, and is based on the unique mating and cannibalistic behavior of black widow spiders. An efficient balance between local search space utilization and global exploration is made possible by these techniques.

BWO is used in system identification to minimize a cost function, usually the mean squared error (MSE) between the response predicted by a mathematical model and the actual system response. The lowest possible MSE is associated with the ideal set of parameters. As a population-based, stochastic optimizer, BWO is particularly useful for locating complicated systems where traditional deterministic methods frequently fall short or converge too soon.
Empirical research shows that BWO often outperforms popular metaheuristic techniques like Differential Evolution (DE), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) in tasks like general parameter estimation, nonlinear system modeling, and IIR filter parameter tuning. BWO's primary benefits include:
Mutation operators and cannibalism were used to gain powerful worldwide search capabilities.
implementation simplicity with minimal control settings.
dependable convergence for issues involving both linear and nonlinear models.
Because of these advantages, BWO is regarded as a reliable substitute for system identification, especially when dealing with complex model structures and noisy data.

4. Experimental Configuration
For evaluation, three benchmark IIR systems from [1] are used:
Example 1: A system of the second order.
Parameters: Number of People: 30 Switch Interval: Every 50 iterations; Maximum Iterations: 500 BWO (mutation rate): 0.3Alpha Guidance: Decline in Linear Form
Table-1 Experimental data

Parameter	GWO-BWO
Population Size	30
Max Iterations	500
Switch Interval	Every 50 iters
Mutation Rate	0.3 (BWO)
Alpha Guidance	Linear decay

5. Findings and Conversation
The performance of an unknown system identification problem has been compared through extensive simulations using the GA, PSO, FPA, and GWO-BWO algorithms. The performance of these relevant algorithms is evaluated by considering three popular benchmark systems. In this instance, the unknown system is imitated by a system of the same order as the benchmark system. A comparison has been made between the simulation results' mean square error and convergence profile. Several simulations have been performed using different sets of control settings for the relevant algorithm.

Example 1 A second order system is considered as referred in [17] and its transfer function is given by

$$H_p(z) = \frac{0.05 - 0.4z^{-1}}{1 - 1.1314z^{-1} + 0.25z^{-2}}$$

This second order system is modelled using a second order unknown system with transfer function

$$H_{af}(z) = \frac{b_0 - b_1 z^{-1}}{1 - a_1 z^{-1} - a_2 z^{-2}}$$

The goal is to optimize the unknown system's numerator and denominator coefficients, b_0, b_1, and a_1, a_2 respectively, so that their values converge to the conventional benchmark function. Table II provides an overview of the coefficients that, when combined with GA, PSO, FPA, and GWO-BWO, result in the best approximation to the second order unknown system. In comparison to GA, PSO, and FPA, the GWO-BWO provides the best approximation to the unknown system coefficients, according to observation Table II. Mean square error (MSE) is statistically analyzed in terms of best, worst, average, and standard deviation to evaluate the effectiveness of the employed method.

Table-2 Comparison Results

Method	Best MSE (Ex.1)	Avg. MSE	Std Dev	Convergence
GA	2.7e-3	1.44e-2	1.07e-2	Slow
PSO	3.2e-7	6.19e-5	6.77e-5	Medium
FPA [1]	9.6e-9	1.83e-5	3.54e-5	Fast
GWO-BWO	**2.88e-9**	**7.34e-6**	**2.13e-5**	**Very Fast**

In all three benchmark examples, the hybrid algorithm surpassed others in convergence speed and final accuracy. Unlike PSO or GA, the GWO-BWO maintained a better balance of exploration and refinement. GA, PSO, and FPA were compared to the GWO-BWO algorithm. It continuously produced quicker convergence and lower MSE values. Example (Example 1: Best MSE): FPA: 9.6e-9, GA: 2.7e-3, PSO: 3.2e-7, GWO-BWO: 2.88e-9. These findings demonstrate that the synergy between GWO and BWO allows the hybrid algorithm to attain higher accuracy and speed.

6. CONCLUSION

This work proposes a new hybrid evolutionary technique for estimating the parameters of IIR filters: Grey Wolf Optimization–Black Widow Optimization (GWO-BWO). The hybridization creates a more balanced and effective search approach by effectively combining the exploration and exploitation capabilities of GWO and BWO. The suggested method outperforms conventional optimization methods like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), as well as the recently created Flower Pollination Algorithm (FPA), in terms of estimation accuracy, convergence speed, and robustness, according to extensive simulation studies conducted on benchmark systems. These results confirm the GWO-BWO method's efficacy as a potential technique for resolving challenging parameter estimation issues in digital signal processing.

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