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REVIEW

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Adaptive IIR model identification using chaotic opposition-based whale optimization algorithm

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Abstract

Infinite impulse response (IIR) filter system recognition is a serious issue nowadays as it has many applications on a diversity of platforms. The whale optimization algorithm (WOA) is a novel nature-motivated population-based meta-heuristic algorithm where the hunting techniques of humpback whales are implemented to solve many optimization problems. But the main disadvantage of WOA is its stagnant convergence rate. As the algorithm is population based, the initialization process is very important in finding the best result and to enhance the convergence rate. In this paper, a novel chaotic oppositional-based initialization process is nominated before the start of conventional WOA to improve the performance. To effectively cover the entire search region, a chaotic-based logistic population map consists of both the actual numbers and its corresponding opposite numbers are incorporated into this opposition-based initialization process. When checked out with some classic model of examples, simulation performance authorizes chaotic oppositional-based whale optimization algorithm (COWOA) as a more convenient contender compared to the other evolutionary techniques in terms of accuracy and convergence speed. Convergence profile and mean square error are the performance specifications that are needed to inspect the performance of our recommended algorithm.

Keywords: Adaptive IIR filter, Meta-heuristic algorithm, Whale optimization algorithm (WOA), Chaotic oppositional-based whale optimization algorithm (COWOA), System identification

Introduction

A digital filter rejects unwanted frequencies from the input signal and allows to pass only the desired frequencies [1]. Digital filters have many advantages over analog filters [2, 3] like flexibility, high reliability, easy to built-in large-scale integration circuits, quick processing, fast recovery time etc. The frequency response of digital filters can be changed by altering its coefficients. A digital filter transfer function can be realized in either a recursive form or a non-recursive form [4]. IIR filter is preferable over FIR filter [5–8] as its implementation involves fewer parameters, requires less memory and low cost, has lower computational complication and has less execution time.

IIR filter is used in image processing [9], communication [10], control systems [11], signal processing [12], and to solve different problems regarding the identification of the unknown plant model [13]. For ideal recognition of system performance, it is very important to find out the convenient filter coefficients to implement the error surface between the filter's output and unknown model's output to accomplish the optimized value.

It is very difficult to optimize the IIR filter's coefficient, as they can be very easily captured within the local minima. This is because the IIR filter provides multimodal error surfaces [14]. In order to reduce this complication, researchers and developers are nowadays trying to use adequate, profitable and powerful nature-inspired transformative meta-heuristic optimization techniques [15–30] for identification of IIR filter. Yao et al. proposed the genetic algorithm (GA) that depends on the principles of genetics and ordinary choice [15], where the parameters of the system are considered as chromosomes of individuals in a population of solutions, but it is affected by improper selection of fitness function, poor mutation and crossover rate. Karaboga used the artificial bee colony (ABC) algorithm based on the intelligent foraging behavior of honey bee swarm [16] for system identification of adaptive filter. But ABC suffers from few difficulties like slow convergence rate during sequential processing, deficient local search capability and large number of objective function calculation. Krusienski et al. introduced a new optimization technique [17] in which problem formulations are solved by a population of candidate solution and these particles move within a search space with respect to the particle's position and velocity. Chen et al. suggested another method [18] in which each particle has a memory in which the local best position determined by itself and the global best position determined by the neighbors are stored. In both [17] and [18], proposed particle swarm optimization (PSO) algorithm converges much before the relevant results; it has issues during the finding of best global minimum and can cause a problem of being captured in a local minima. Dai et al. used the seeker optimization algorithm (SOA) for IIR system identification problem [19] in which experimental and observational gradients control the search direction by estimating the response with respect to the position changes though it is not perfectly proved on a immense area of benchmark functions. Inspite of difficulties like stagnant convergence rate and being stuck in local minima during the last iterations, gravitational search algorithm (GSA) was successfully applied for IIR model identification by Rashedi et al. [20], in which unknown filter coefficients are termed as a vector space that can be improved. It obeys the laws of Newtonian and mass interactions. Panda et al. introduced another swarm-based algorithm [21], namely cat swarm optimization (CSO), that impersonates the normal attitude of cats. But CSO is convenient for pint-sized population only. When the population size enhances, the convergence rate becomes slower. Depending on the echolocation characteristics of bats, a nature-inspired meta-heuristic algorithm, namely bat algorithm (BA), was introduced. Saha et al. modify the original BA [22] by using action-based opposite numbering concept for the recognition of IIR system identification to enhance the convergence speed and performance, though the optimization precision is poor and convergence speed is slow during the later span. Ashok et al. utilize the pollination process of flower to optimize the filter coefficients. Flower pollination algorithm (FPA) [23] improves the fitness value, but it has weakness towards immature convergence and feeble exploitation capability. Upadhyay et al. introduced another method inspired by brightness of the fireflies [24] in which the position of the brightest firefly is used to find the optimum solution. But it undergoes with unidirectional low exploration capability. The work of Sen et al. points out the effectiveness of the grey wolf optimization (GWO) algorithm with a ranking-based mutation operator for IIR system identification [25], though it suffers from gradual convergence rate and may be captured into local optima. Humaidi et al. merged the least mean square (LMS) algorithm with GA [26] to avoid the local optima problem of IIR filter identification. To upgrade the local search choice of adaptive IIR model, Durmus et al. suggested a new mechanism [27] namely self-adaptive search-equation-based artificial bee colony (SSEABC), in which an equation is randomly calculated with the help of a self-adaptive mechanism. Singh et al. suggested a teacher–learner-based optimization (TLBO) algorithm [28] for solving the IIR system identification problem, which is inspired by the classroom environment. TLBO is a moderate method and requires lot of memory space. A modified PSO [29] is suggested by Chang with a numerous number of subpopulations which can evaluate the IIR filter coefficients to solve the multimodal error surface problem, yet balance between the exploration and exploitation phases depends on the velocity and position equations of the PSO algorithm. WOA [30] was first proposed by Mirjalili et al., in which the behavioral characteristic of a humpback whale is implemented. WOA is further modified by Luo et al. [33] in which an integrated ranking-based variation operator is used to increase the convergence speed of conventional WOA. In both [30] and [33], the algorithm suffers from slow convergence rate and poor solution efficiency. Yang et al. proposed a chaotic-based method [34] which is very sensitive to its primary conditions. Oliva et al. utilizes this improved chaotic process [35] to estimate the parameters of a photovoltaic cell.

Our work has been primarily focused on presenting a comparative study of fitness values between seven meta-heuristic algorithms, namely BA, PSO, GA, WOA, chaotic improved harmony search (CIHS), cellular particle swarm optimization–differential evolution (CPSO-DE) and our proposed COWOA. Out of all the algorithms, WOA and COWOA is thoroughly studied in this work. In our proposed method, a chaotic oppositional-based initialization process is introduced to improve the initialization process, convergence rate and performance of the ordinary WOA. In this work, the COWOA is applied to three different examples of IIR model identification problem with same or reduced-order and is compared with some other existent nature-inspired evolutionary optimization algorithms and conventional WOA. The novelties of the present article are listed below:

- An optimal IIR filter model is developed by tuning the coefficient of the transfer function of adaptive IIR filter in order to reduce the difference between the output of the unknown plant and adaptive IIR filter for the same white Gaussian noise input.
- To enhance the convergence mobility and robustness and to cover the entire search region, oppositional-based learning (OBL) and chaotic approach are integrated with the WOA and the hybridized COWOA has been adopted to enhance the performance of adaptive IIR model identification problem.

- A detailed analysis of WOA and COWOA algorithms is presented to analyze both same-order and reduced-order IIR models.

The remaining portion of the paper is organized as follows: In section "Description of the problem", the problem formulation is clearly described. In section "Whale optimization algorithm", we represent and elaborate the WOA steps. In section "Chaotic oppositional-based algorithm", we present the improvement in the initialization process of WOA by our proposed chaotic opposition-based methodology. The examples, simulation results and analysis are discussed in section "Simulation results and discussion". Finally, conclusion is described in section "Conclusion".

Description of the problem

Generally, for dynamic systems, the output response is dependent on the present or instantaneous value of the input response and also on the system's past behavior. Dynamic system modeling can be performed in both continuous and discrete time forms. Here we will be dealing with discrete time form.

Here, the IIR filter coefficients are tuned till the output signal of the unknown system comes almost closer to the IIR filter's output response, when both the IIR filter and the unknown system are excited by the same input. The block diagram depicting the adaptive IIR system identification problem using standard optimization techniques is shown in Fig. 1.

If we consider the input to the system as $X(z)$[or $x(n)$], the output response as $Y(z)$[in the time domain as $y(n)$] and the impulse response as *h(k)*, the convolution relation for IIR systems can be given by:

$$y(n) = \sum_{k=0}^{\infty} h(k).x(n-k) \tag{1}$$

Since the weighted sum includes the present and all past input responses of the dynamic system, an inference as IIR systems possess an infinite memory can be drawn. A

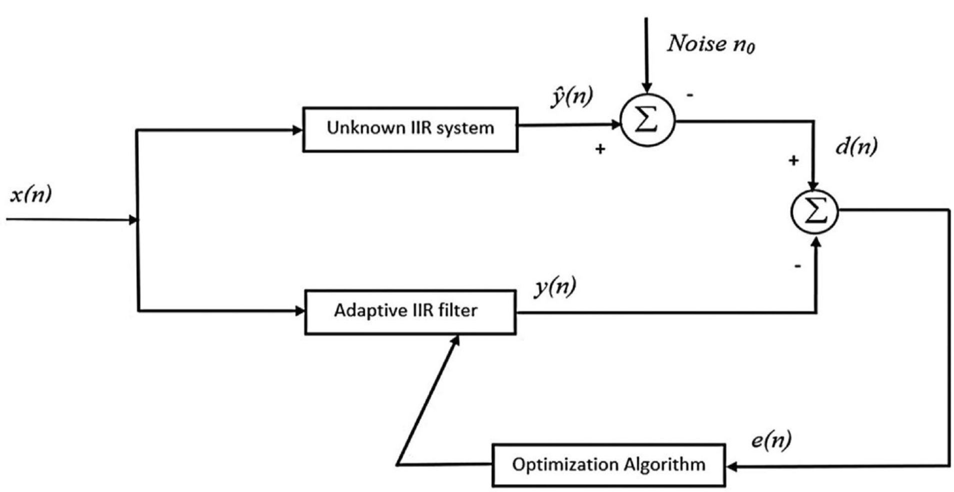

Fig. 1 Block representation of the adaptive IIR system

system is termed as recursive when the product response or output $y(n)$ at any discrete time n believes in current input and previous values of both input and output responses.

The following differential equation can describe an IIR system:

$$y(n) = \sum_{k=1}^{N} a_k y(n-k) + \sum_{k=0}^{M} b_k x(n-k) \tag{2}$$

where a_{k} and b_{k} are two coefficients for the design of IIR system transfer function.

Taking Z-transform of the above equation on both sides we get:

$$Y(z) = \sum_{k=1}^{N} a_k z^{-k} Y(z) + \sum_{k=0}^{M} b_k z^{-k} X(z) \tag{3}$$

The generalized transfer function of an IIR system is given by:

$$\frac{Y(z)}{X(z)} = H(z) = \frac{\sum_{k=0}^{M} b_k z^{-k}}{1 + \sum_{k=1}^{N} a_k z^{-k}} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_M z^{-M}}{1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_N z^{-M}} \tag{4}$$

The equations for $Y(z)$ and $H(z)$ mentioned above can be expressed as a computational procedure to determine the $y(n)$, the output sequence from the input sequence $x(n)$.

It should be noted here that for all models, unknown plant's transfer function is considered as $H_p(z)$ and $H_m(z)$ as the transfer function of the adaptive IIR model.

The comprehensive feedback of an unknown IIR plant is stated by the following equation:

$$d(n) = \hat{y}(n) + n_0 \tag{5}$$

where $\hat{y}(n)$ is the output response of unknown plant and n_0 is the additive white gaussian noise (AWGN).

The error signal $e(n)$ and mean squared error (MSE) can be defined as:

$$e(n) = d(n) - y(n) \tag{6}$$

$$MSE = J(\omega) = \frac{1}{N} \sum_{n=1}^{N} (e^2(n)) \tag{7}$$

where, N implies the number of input samples for the computation of aspiration or fitness operation. So, in this research work, our main objective is to minimize the error objective value, $MSE = J(\omega)$ by properly tuning the coefficient vector ω of the transfer function of adaptive IIR filter in order to reduce the difference between the output of the unknown plant and adaptive IIR filter for the same white gaussian noise input. The coefficient vector ω of the transfer function is defined as below:

$$\omega = [a_0 a_1 \ldots a_N b_0 b_1 \ldots b_M]^T \tag{8}$$

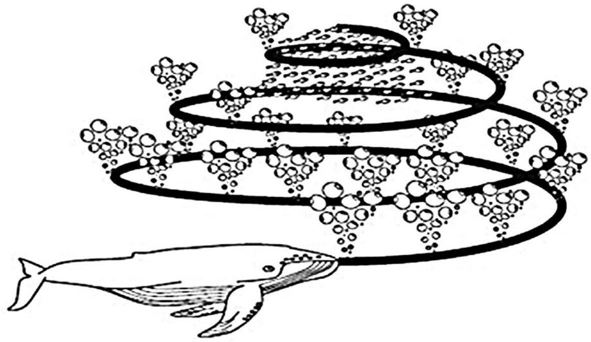

Fig. 2 Bubble net feeding behavior of humpback whales

Whale optimization algorithm

WOA is a noble meta-heuristic population-based algorithm [30] proposed by Mirjalili et al.. The bubble-net attacking method followed by all the humpback whales to catch their prey (shown in Fig. 2) is what WOA takes into account for simulation purposes. Humpback whales generally hunt near the water surface of the ocean. The exploration is made by generating extraordinary and peculiar bubbles along a '9'-shaped or circular path. There are two movements found correlated with bubble, namely 'upward-spiral' and 'double loops' or 'coral loop' or 'capture loop.' They fall around 12–15 m down the sea surface and then start to create bubbles along the circular path encompassing the target and eventually floats to the surface.

Encircling prey

A humpback whale has the ability to recognize the prey's presence, and after recognizing, it encircles the target. The optimal position of the prey being unknown at first present optimal solution nearer to the possible solution is considered by the WOA algorithm. After evaluation of the best optimum solution, other search agents try updating their position toward the best search agent for achieving the present best position, which is mathematically represented as [30]:

$$\overrightarrow{D} = \beta.\overrightarrow{X^*}(t) - \overrightarrow{X}(t) \tag{9}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X^*}(t) - \alpha.\overrightarrow{D} \tag{10}$$

where, current iteration is expressed as t, the position vector of the current best arrangement at tth iteration and each search agent's position vector are $\overrightarrow{X^*}(t)$ and $\overrightarrow{X}(t)$, respectively. α and β are two coefficients. From (9) and (10), the current position vector of the optimum measure is represented by $\overrightarrow{D}$. Upgrading $\overrightarrow{X^*}$ at each and every cycle should be performed, if a superior solution co-exists.

The coefficients are given as [30]:

$$\alpha = 2.m.n - m \tag{11}$$

$$\beta = 2.n \tag{12}$$

The value of α is in the range $[-m, m]$ where the value of m linearly decreases from 2 to 0 throughout the entire exploration and exploitation cycles. m is calculated as $m = 2 - 2 * t/t_{\max}$. m remains same throughout the entire cycle. n is a random number in the range [0, 1]. $t_{\max}$ is the maximum number of allowed iterations.

Bubble-net attacking method (exploitation phase)

To methodically model the aforementioned attacking mechanism, two different mechanisms have been discussed in the following sections.

Shrinking enriching mechanism

The main objective of this mechanism is to lower down the estimated value of *m*, so as to initiate the behavior of humpback whales. Therefore, α is also decreased in order to *m*. The random values for a vector α are set in the range of [−1, 1]. The updated position of the search agent can be characterized anywhere within the search space bounded by the agent's best position and position of best agent chosen currently, just by setting the random values of α. Figure 3 illustrates all plausible positions starting from *(X, Y)* towards *(X*, Y*)*, which is achievable through $0 \leq \alpha \leq 1$ in a two-dimensional space.

Spiral updating position

Here, distance from *(X,Y)* to the target's location at *(X*, Y*)* is first evaluated and then a resemblance to the helical development for humpback whales is created using a spiral equation, deduced within the space defined by the positions of whale and prey.

$$\overrightarrow{D} = \overrightarrow{X^*}(t) - \overrightarrow{X}(t) \tag{13}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{D}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) \tag{14}$$

where, the maximum span between the *i*th whale and the prey is $\overrightarrow{D}$, *b* is a constant defining the shrinking spiral logarithmic illustration of (14). *l* defines a number arbitrarily chosen within [−1, 1]. A 50% probability is chosen for either the shrinking encompassing

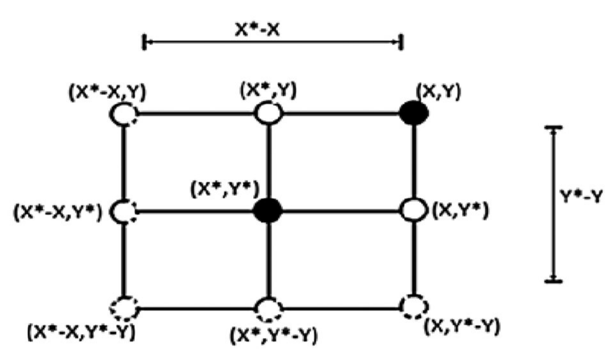

Fig. 3 Possible positions of (X,Y) and (X*,Y*)

method or spiral path model for updating the position of whales during execution. The structure is modeled as:

$$\overrightarrow{X}(t+1) = \overrightarrow{X^*}(t) - \alpha.\overrightarrow{D}, \quad \text{if p} < 0.5 \tag{15}$$

$$= \overrightarrow{D}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t), \quad \text{if p} \geq 0.5 \tag{16}$$

The decision regarding the particular procedure being selected is modeled with random number $p \in [0, 1]$, which subjects to a uniform distribution. The agents proceed toward the leader on the basis of shrinking encircling procedure if $p < 0.5$. For $p \geq 0.5$, the search agent location is updated by spiral updating position.

Searching for prey (exploration phase)

α facilitates exploration to seek a prey, its value being either greater than 1 or less than −1. When the condition $\alpha \geq 1$ is met, exploration is imposed onto the humpback whales to figure the global optimum and discard many local minima. So, mathematically derived model required for this phase is as follows:

$$\overrightarrow{D} = \beta.\overrightarrow{X_{rand}} - \overrightarrow{X} \tag{17}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_{rand}}(t) - \alpha.\overrightarrow{D} \tag{18}$$

where, $\overrightarrow{D}$ denotes the distance between the ith whale and the prey and $\overrightarrow{X_{rand}}$ defines an arbitrary position vector or any randomly sorted out whale from the currently considered community. The flowchart of WOA is illustrated in Fig. 4.

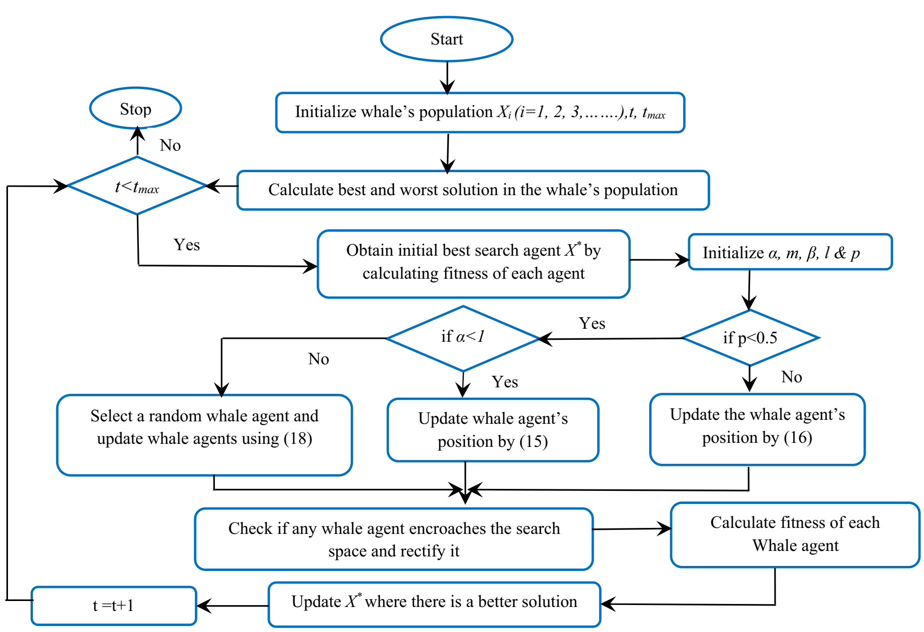

Fig. 4 Flowchart of WOA

Chaotic oppositional-based algorithm

The word 'chaotic' has been derived from 'chaos,' i.e., characteristics of a system, specifically complex system whose nature is totally unpredictable and irregular. Chaotic maps are nowadays widely introduced in such optimization algorithms where search space is to be explored. In meta-heuristic algorithms, haphazardness is attained by using probability distribution functions. It is possible to replace such a haphazardness by chaotic maps. In our proposed work, ten different chaotic maps [36] are considered in the proposed COWOA approach to tune the controlled parameters of adaptive IIR model identification problem obtained by oppositional-based WOA technique. These ten chaotic maps have different chaotic phenomenon, which are individually tested to obtain the optimal solution. It has been observed that among ten chaotic behavior, Gaussian map provides the optimal solution. Since the results obtained with gaussian map are significantly better as compared to other chaotic maps, the whole simulation is performed with the gaussian chaotic map.

Definition (opposite number): Assume, $x \in [u, v]$ to be a real number. Then $\overline{\boldsymbol{x}}$ being considered as an opposite number to x can be defined by a mathematical equation as:

$$\overline{x} = u + v - x \tag{19}$$

Definition (opposite point): Assume $P = (x_1, x_2, ..., x_k)$ to be a point in the K-dimensional search space, where, $x_i \in [u_i, v_i]$, $(i = 1, 2, 3, 4, ...k)$. Therefore, opposite point $\overline{P} = (\overline{x}_1, \overline{x}_2, ..., \overline{x}_k)$ can be stated mathematically as:

$$\overline{x}_i = u_i + v_i - x_i \tag{20}$$

Oppositional-based population initialization

Consider $P = (x_1, x_2, ..., x_k)$ as a particular point in K-dimensional search space (i.e,. a whale solution) suggested by Rahnamayan et al. [37]. Let us assume that f(.) be a fitness function that can be utilized to evaluate the whale's fitness. As per the explanation of opposite point mentioned a priori, $\overline{P} = (\overline{x}_1, \overline{x}_2, ..., \overline{x}_k)$ is the opposite point of $P = (x_1, x_2, ..., x_k)$.

The point P might be replaced by $\overline{P}$ only if the condition $f(\overline{P}) \geq f(P)$ is met, else we have only one option that is to continue with point P; hence, we can calculate the point and its symmetrically opposite counterpart simultaneously to make a decision to choose the best one.

Thus, when there is no earlier knowledge about the solution, better initial whale solution, namely opposite population (OP) can be accessed using opposite points. This proposal was first recommended and implemented on combined heat and power dispatch system [38] by Roy et al.. Initialization of OP is described by the following algorithm:

for $i = 1 : N_P$ *(N_P = total population size)*

  for $j = 1 : N_C$ *(N_C = number of control variable)*

    $OP_{i,j} = u_i + v_i - P_{i,j}$

  End for

End for

Chaotic opposition based initial population

Sundaram [39] offered a technical approach where the chaotic maps are used to initialize the population to increase the population diversity of the search space by deriving the search space information, as the initial condition of chaotic maps is very sensitive and random in nature.

Therefore, this paper approaches a noble initialization technique that binds together the effectiveness of chaotic systems and strategies of opposition-based learning in order to determine the initial population. To achieve this, a logistic map is selected.

$$ch(i+1) = \sigma * ch(i) * (1 - ch(i)) \tag{21}$$

where $ch(i) \in (0,1)$,$i = 0, 1, 2, ...PD$; i is the iteration number; PD is the total number of variables; σ is the chaotic control parameter; ch is the chaotic variable. Depending on the logistic map and dependence of it on chaotic variable, a number can be defined in terms of its maximum and minimum number of dimensional space used in population initialization.

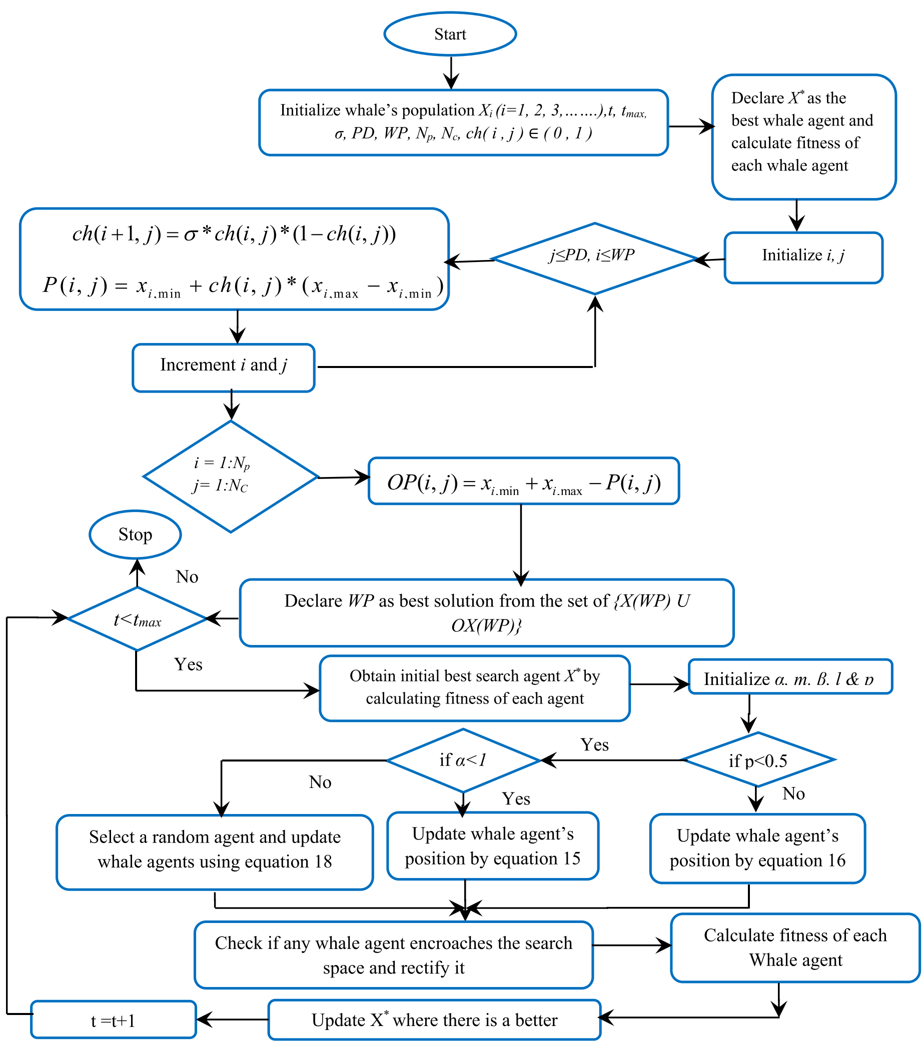

Figure 5: Flowchart of COWOA

Fig. 5 Flowchart of COWOA

$$P(i) = x_{i,\min} + ch(i) * (x_{i,\max} - x_{i,\min}) \tag{22}$$

Verify that there are no dualistic individuals inside the community. This logic does not make fully sure that no indistinguishable exist, but any twins that are found are randomly modified, so there must be a very good prospect that there are no equivalents after this strategy. The flowchart of COWOA is illustrated in Fig. 5.

Pseudo code of our proposed approach COWOA

```
Initialize the whale population X (i,j)
Initialize σ, ch, PD, WP, Np, Nc
X* =best whale agent
Calculate the fitness of each whale agent
Randomly initialize variables ch (i,j) ∈(0,1);
Set the counter j = 1, i=1;
//chaotic opposition based initialization
  While( j ≤ PD ) do
      While (i ≤ WP ) do
          ch(i+1, j) = σ * ch(i, j) * (1 − ch(i, j));
          X(i, j) = x_{i,min} + ch(i, j) * (x_{i,max} − x_{i,min});
          Set i=i+1 & j=j+1;
      End while
  End while
  for i=1:Np
      for j=1:Nc
          OX(i, j) = x_{i,min} + x_{i,max} − X(i, j);      //OX (i,j)opposite of initial X (i,j)
      End for
  End for
//end of chaotic opposition based initialization
Select WP a fittest individual from set of {X (WP) U OX (WP)} as initial whale population.
  While t<t_max
      for each whale agent
          Update m, α, β, l and p;
          Randomly initiate variables p ∈ (0,1);
          if (p<0.5)
              if (α⃗ <1)
                  Update position of current whale agent by (15)
              Else if (α⃗ ≥1)
                  Select a random whale agent (X_rand);
                  Update position of current whale agent by (18)
              End if.
          Else if (p>=0.5)
              Update position of current whale agent by (16)
          End if.
      End for.
      Check if any whale agent interrupts the search space and modify it.
      Calculate fitness of each whale agent.
  End while.
Update X* if there is a better solution.
```

Simulation results and discussion

The effectiveness of the proposed COWOA in designing digital IIR filters has been discussed in this section through 6 simulation instances, and the outcomes are compared with some other meta-heuristic optimization algorithms for a detailed analysis. Our proposed chaotic oppositional-based whale optimization algorithm performs more efficiently, and it provides better simulation results than some of the other meta-heuristic algorithms like PSO [40], GA [41], BA [42], chaotic improved harmony search (CIHS) [43], WOA [30] and cellular particle swarm optimization–differential evolution (CPSO-DE) [45]. Our proposed COWOA algorithm's parameters are tuned for thirty different trials for simulation instance 1. During the tuning of the parameters, we were concerned with the best objective value achieved so far and their corresponding computation time in seconds. The same tuned value of the parameters is used throughout our experiment to achieve the best possible fitness value and minimum computation time. The simulations are carried out using MATLAB 2016a and in a laptop with configurations as, 8 GB of RAM, i5 processor and a clock speed of 2.11 GHz.

Simulation studies are implemented on three different examples, which are taken from [16, 21, 39, 44]. The simulation results include best, worst, mean and standard deviation values of mean square error or MSE for all models including same and reduced orders. The filter parameters for both the same and reduced orders are evaluated also. Each simulation instance of the proposed algorithm, along with the comparative counterparts, is executed for 30 independent times.

White Gaussian noise signal having zero mean, unit variance and uniform distribution serve as an input to the systems that have been discussed in the following sections.

An unknown plant can be designed in two different ways:

I. Same-order plant and same-order filter.
II. Same-order plant and reduced-order filter.

For all test cases that have been considered in this research, 'a's are the numerator coefficients and 'b's are considered as denominator coefficients of the filters both for the same and reduced order models. The ultimate results obtained in terms of objective value, convergence speed and root mean squared error, i.e., RMSE, are given in the successive sections both for the same and reduced orders of the IIR filters. Also estimated and actual parameters i.e. filter coefficients, the mean squared errors are also presented in this work for the actual order of IIR plants.

***MODEL 1*:**

For model-1, a 3rd-order plant is chosen whose transfer function is given by:

$$H_p(z) = \frac{-0.2 - 0.4z^{-1} + 0.5z^{-2}}{1 - 0.6z^{-1} + 0.25z^{-2} - 0.2z^{-3}} \tag{23}$$

(a) CASE 1: In this case, transfer function of an adaptive filter model where a 3rd-order plant $H_p(z)$ is modeled using a 3rd–order IIR filter $H_{SOM}(z)$ is given by:

$$H_{SOM}(z) = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2}}{1 - b_1 z^{-1} - b_2 z^{-2} - b_3 z^{-3}} \tag{24}$$

(b) CASE 2: A 3rd-order plant $H_p(z)$ can be modeled by using a 2nd-order IIR filter $H_{ROM}(z)$; therefore, transfer function of adaptive IIR filter is thus assumed as:

$$H_{ROM}(z) = \frac{a_0 + a_1 z^{-1}}{1 - b_1 z^{-1} - b_2 z^{-2}} \tag{25}$$

MODEL 2:

For model-2, a 4th-order plant is chosen whose transfer function is given by:

$$H_p(z) = \frac{1 - 0.9z^{-1} + 0.81z^{-2} - 0.729z^{-3}}{1 + 0.04z^{-1} + 0.2775z^{-2} - 0.2101z^{-3} + 0.14z^{-4}} \tag{26}$$

(a) CASE 1: In this case, transfer function of an adaptive filter model where a 4th-order plant $H_p(z)$ is modeled using a 4th-order IIR filter $H_{SOM}(z)$ is given by:

$$H_{SOM}(z) = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}}{1 - b_1 z^{-1} - b_2 z^{-2} - b_3 z^{-3} - b_4 z^{-4}} \tag{27}$$

(b) CASE 2: In this case, transfer function of an adaptive filter model where a 4th-order plant $H_p(z)$ is modeled using a 3rd-order IIR filter $H_{ROM}(z)$ is given by:

$$H_{ROM}(z) = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2}}{1 - b_1 z^{-1} - b_2 z^{-2} - b_3 z^{-3}} \tag{28}$$

MODEL 3:

For model-3, a 5th-order plant is chosen whose transfer function is given by:

$$H_p(z) = \frac{0.1084 + 0.5419z^{-1} + 1.0837z^{-2} + 1.0837z^{-3} + 0.5419z^{-4} + 0.1084z^{-5}}{1 + 0.9853z^{-1} + 0.9738z^{-2} + 0.3864z^{-3} + 0.1112z^{-4} + 0.0113z^{-5}} \tag{29}$$

(a) CASE 1: A 5th-order plant $H_p(z)$ can be modeled by using a 5th-order IIR filter $H_{SOM}(z)$, therefore transfer function of adaptive IIR filter is thus assumed as

$$H_{SOM}(z) = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4} + a_5 z^{-5}}{1 - b_1 z^{-1} - b_2 z^{-2} - b_3 z^{-3} - b_4 z^{-4} - b_5 z^{-5}} \tag{30}$$

(b) CASE 2: In this case, transfer function of an adaptive filter model where a 5th-order plant $H_p(z)$ is modeled using a 4th-order IIR filter $H_{ROM}(z)$ is given by:

$$H_{ROM}(z) = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4}}{1 - b_1 z^{-1} - b_2 z^{-2} - b_3 z^{-3} - b_4 z^{-4}} \tag{31}$$

The objective of the COWOA algorithm is to effectively optimize the filter parameters (numerator and denominator coefficients) for all the possible test cases.

Simulation of filter parameters and MSE results related to this work are elaborated in the following sections.

Simulation instance-1

Optimal filter parameters achieved by COWOA and other state-of-the-art algorithms for this simulation instance are displayed in Table 1. The first simulated instance includes tabulated results of MSE values in Table 2 based on 3rd-order plant and a 3rd-order IIR filter (model-1 case-1), where both the known plant's order and unknown IIR filter's order are chosen to be same. For this case, the calculated mean value of MSE of our proposed COWOA algorithm is 1.190E−03,whereas for BA it is 2.9E−02, for PSO it is 3.7E−03, for GA it is 2.5E−03, for WOA it is 1.6E−03 and for CIHS it is 6.9E−03. The same trend is observed while comparing standard deviation value (1.802E−04) of COWOA with those achieved by other algorithms. The graphical comparative study of COWOA and WOA in Fig. 6 with MSE as the ordinate and number of iterations as the abscissa also provides satisfactory results in two aspects. The rate of convergence of COWOA achieved is much higher than that of WOA, which is the main concern of our work. The second important aspect from the figure is that for both algorithms, i.e., COWOA and WOA, respective MSE values, 1.0081E−03 and 1.4557E−03 obtained at the 100th iteration conforms with the best values of MSE from Table 2.

Simulation instance-2

The second simulated instance computes MSE results for a model based on 3rd-order plant and a 2nd-order IIR filter (i.e., model-1 case-2). Optimal coefficients realized by our proposed COWOA and other meta-heuristic algorithms are shown in Table 3. The results so obtained are arranged inside Table 4, and from each value given in the tables, the effectiveness of COWOA can be deducted in comparison to BA, PSO, GA and WOA. Average MSE values for COWOA, BA, PSO, GA, CIHS, CPSO-DE and WOA are 1.167E−03, 7.70E−03, 1.40E−03, 3.259E−02, 6.82E−03, 7.3E−03 and 1.244E−03, respectively. Standard deviation of MSE for COWOA is 6.984E−05, which is compared to other algorithms as given in Table 4. From the comparative study of the convergence graphs of COWOA and WOA (Fig. 7) it can be proved that COWOA converged from 39th iteration onwards which generates the best value of MSE as 1.097E−03, while on the other hand, WOA converged from 60th iteration onwards to provide the best value as 1.156E−03. From these data, it can be predicted that our proposed COWOA algorithm has improved performance and minimum MSE value with early convergence than BA, PSO, GA and WOA.

Simulation instance-3

In the third simulation instance, which includes a model of 4th-order plant and 4th-order IIR filter (model-2 case-1), the proposed COWOA provides a better convergence rate and quality of solution and outperforms the other algorithms. Table 5 represents the optimal parameters obtained by our proposed COWOA and other evolutionary optimization techniques for this simulation instance. Mean MSE and

Table 1 Optimal parameters achieved by COWOA and other meta-heuristic algorithms for simulation instance1

Parameter	Actual value	Estimated value				
		BA [33]	PSO [33]	WOA	COWOA	GA [21]
a_0	−0.20	−0.2021	−0.1688	−0.2633	−0.2009	−0.2258
a_1	−0.40	−0.4071	−0.4388	−0.6530	−0.6268	−0.2717
a_2	0.50	0.4939	0.4283	0.2208	0.1016	0.4643
b_1	0.60	0.5804	0.5000	0.4253	0.3924	0.7742
b_2	−0.25	−0.2494	−0.2508	−0.4241	−0.4076	−0.4379
b_3	0.20	0.1908	0.1812	0 .0936	0.1825	0.3206

Table 2 Statistical analysis of COWOA and other meta-heuristic algorithms for simulation instance1

Fitness	BA [33]	PSO [33]	WOA	COWOA	CIHS [43]	GA [21]
Best	7.70E−07	2.65E−04	1.45E−03	1.008E−03	6.2E−03	0.73E−03
Worst	8.08E−02	7.10E−03	3.86E−03	2.712E−03	8.6E−03	6.15E−03
Mean	2.09E−02	3.70E−03	1.61E−03	**1.190E−03**	6.9E−03	2.51E−03
Std	1.75E−02	1.60E−03	2.56E−04	**1.802E−04**	7.1E−04	1.48E−03

The bold values confirm the superiority of the result of our propoed COWOA approach

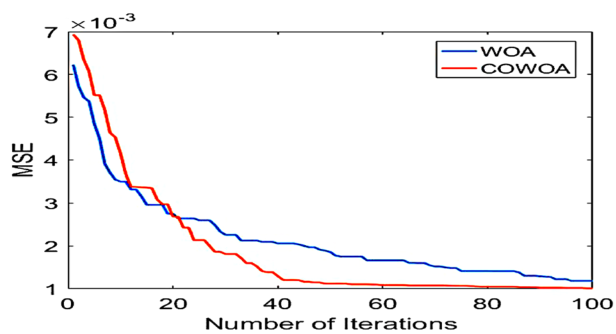

Fig. 6 MSE curves for simulation instance 1

standard deviation for COWOA (Table 6) which have been calculated as 1.676E−02 and 3.357E−03 respectively are quite less, which clearly suggest that COWOA does not get stuck at local optima unlike algorithms like WOA, BA, PSO and GA listed in Table 6 and minimizes the mean squared error as much as possible, thereby allowing us to consider COWOA as a suitable algorithm for optimizing digital IIR filter effectively and efficiently (Table 7).

Simulation instance-4

The fourth simulated instance includes the MSE results of model-2 case-2, where a 4th-order plant is modeled with an unknown IIR filter of order 3. The evaluated results are presented in Table 8. It is quite apparent from Table 8 that the mean value of COWOA is 1.612E−02 and the attained standard deviation value (2.1102E−03) is much smaller than the other algorithms, thus dictating the speedy nature of the proposed COWOA algorithm. The mean value of MSE is 6.9E−02, 1.36E−02, 1.08E−01, 4.24E−02 and

4.66E−02 for BA, PSO, WOA, CPSO-DE and GA respectively. The graphical result of this simulation between COWOA and WOA (Fig. 8) shows that COWOA converged from 45th iteration onwards to give the best value of MSE as 3.566 E−02, while on the other hand, WOA converged from 70th iteration onwards to give the best value as 1.031E−01 (Table 9). Therefore, COWOA has a higher rate of convergence than WOA and shows better performance than the other remaining algorithms. Optimal filter coefficients attained by COWOA and other meta-heuristic algorithms for this simulation case are demonstrated in Table 7.

Simulation instance-5

The fifth simulation instance includes the MSE results of model-3 of case-1, and the results are tabulated in Table 10. The model which is chosen for this simulation is a plant of 5th-order and an IIR filter of 5th-order. The mean value of MSE for COWOA evaluated using MATLAB 2016a is 1.1531 E−02 and the standard deviation for COWOA is computed as 1.1394 E−03, which happens to be statistically robust than other algorithms. The mean value of MSE is 2.004E−02, 1.714E−02, 1.361E−01 and 3.399E−02

Table 3 Optimal parameters achieved by COWOA and other meta-heuristic algorithms for simulation instance2

Parameter	Actual value	Estimated value	
		WOA	COWOA
a_0	−0.20	−0.2418	−0.2178
a_1	−0.40	−0.5852	−0.5515
b_1	0.60	0.1790	0.1080
b_2	−0.25	−0.3499	−0.2911

Table 4 Statistical analysis of COWOA and other meta-heuristic algorithms for simulation instance2

Fitness	BA [33]	PSO [33]	WOA	COWOA	CIHS [43]	CPSO-DE [45]	GA [21]
Best	3.69E−04	8.09E−04	1.156E−03	1.095E−03	6.5E−03	5.26E−03	1.65E−02
Worst	2.37E−02	2.90E−03	2.128E−03	2.221E−03	8.1E−03	7.39E−03	6.66E−02
Mean	7.70E−03	1.40E−03	1.244E−03	**1.167E−03**	7.3E−03	6.82E−03	3.25E−02
Std	6.70E−03	4.48E−04	2.821E−04	**6.984E−05**	6.6E−04	3.56E−04	1.61E−02

The bold values confirm the superiority of the result of our propoed COWOA approach

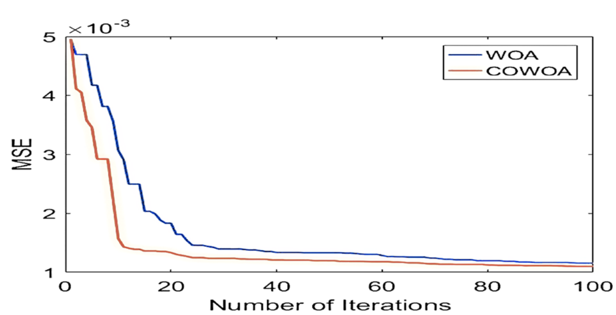

Fig. 7 MSE curves for simulation instance 2

for BA, PSO, WOA and GA respectively. Even from the graphical illustration of Fig. 9, COWOA converged from 62nd iteration onwards to give the best value of MSE as shown in Table 10 and the comparative algorithm, WOA converged from 73rd iteration onwards to give the best value as in Table 10. This instance further strengthens our work on the grounds of high convergence rate achievable through the new and robust COWOA algorithm over others. Optimal filter parameters realized by our proposed technique and few of other popular optimization techniques for this simulation instance are presented in Table 9.

Simulation instance-6

Table 11 represents the optimal coefficients accomplished by proposed COWOA and other meta-heuristic algorithms for simulation instance-6. In this simulation instance, a 4th-order IIR filter is used to model a 5th-order plant (case-2 of model-3) and MSE

Table 5 Optimal parameters achieved by COWOA and other meta-heuristic algorithms for simulation instance3

Parameter	Actual value	Estimated value				
		BA [33]	PSO [33]	WOA	COWOA	GA [21]
a_0	1.00	0.9734	0.7114	1.0000	1.0000	1.0670
a_1	−0.90	−0.7024	−0.8393	−0.8741	−0.2908	−0.7493
a_2	0.81	0.7232	0.8438	0.1635	0.0652	0.7214
a_3	−0.729	−0.5615	−0.6521	−0.0668	−0.0704	−0.4350
b_1	−0.04	−0.2836	−0.0618	−0.0016	−0.4623	−0.2308
b_2	−0.2775	−0.5084	−0.5574	−0.0102	−0.0202	−0.3064
b_3	0.2101	0.0394	0.0021	0.0398	0.2589	0.1065
b_4	−0.14	−0.1734	−0.3692	−0.0121	−0.1004	−0.0489

Table 6 Statistical analysis of COWOA and other meta-heuristic algorithms for simulation instance3

Fitness	BA [33]	PSO [33]	WOA	COWOA	GA [21]
Best	4.55E−04	7.40E−03	1.1374E−01	3.472E−02	0.7158E−02
Worst	2.56E−01	3.42E−02	2.988E−01	1.187E−01	4.4913E−02
Mean	8.19E−02	1.96E−02	1.229E−01	**1.676E−02**	1.7414E−02
Std	4.59E−02	7.10E−03	4.854E−03	**3.357E−03**	1.2255E−02

The bold values confirm the superiority of the result of our propoed COWOA approach

Table 7 Optimal parameters achieved by COWOA and other meta-heuristic algorithms for simulation instance4

Parameter	Actual value	Estimated value	
		WOA	COWOA
a_0	1.00	0.9174	0.9126
a_1	−0.90	−0.5264	−0.9126
a_2	0.81	0.4543	0.6294
b_1	−0.04	−0.0010	−0.0560
b_2	−0.2775	−0.2797	−0.0108
b_3	0.2101	0 .0030	0.0113

Table 8 Statistical analysis of COWOA and other meta-heuristic algorithms for simulation instance4

Fitness	BA[33]	PSO[33]	WOA	COWOA	CPSO-DE[45]	GA[21]
Best	4.05E−04	4.60E−03	1.031E−01	3.566E−02	3.67E−02	1.93E−02
Worst	1.49E−01	2.20E−02	2.115E−01	1.055E−01	4.58E−02	9.25E−02
Mean	6.90E−02	1.36E−02	1.0762E−01	**1.612E−02**	4.24E−02	4.66E−02
Std	3.75E−02	4.70E−03	1.0733E−02	**2.1102E−03**	1.88E−03	2.33E−02

The bold values confirm the superiority of the result of our propoed COWOA approach

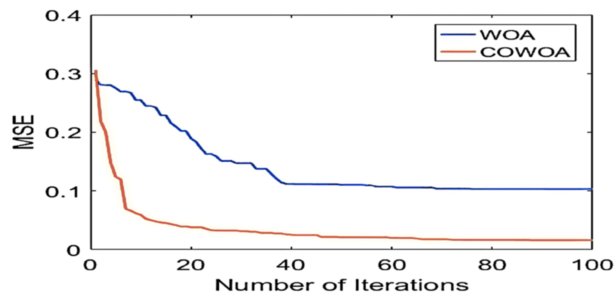

Fig. 8 MSE curves for simulation instance 4

results are calculated and then tabulated in Table 12. After 100 iterations, mean MSE value for COWOA is 1.077E−02 and the standard deviation is 2.140E−03 which are very competitive results over other algorithms whose MSE values are given in Table 12. The mean value of MSE is 4.87E−02, 2.05E−02, 1.29E−02 and 32,386.63 for BA, PSO, WOA and GA respectively. Even from the graphical illustration shown in Fig. 10, the best value of MSE for COWOA i.e., 1.016E−02 is achieved from 52nd iteration onwards compared to WOA, whose best value of MSE which equals 1.2199E−02 is achieved from 80th iteration onwards. Therefore, COWOA has yet again provided evidence that it converges faster and yields better results than WOA and the other algorithms.

Our proposed COWOA provides improved results in all the simulation instances with respect to state-of-the-art algorithms due to the following reasons:

- Chaotic logistic mapping has advantages like acute sensitivity to introductory values, stochasticity, avoiding the local optima and increased convergence rate.
- Among ten chaotic maps, our suggested Gaussian logistic map provides the optimal solution. Gaussian chaotic maps also enhance the population diversity of the search space by evolving the problem space particulars.
- For obtaining better solutions to start with, to increase the convergence rate and to ensure that no solution should be missed from the entire search space, we have substituted random initialization with opposition-based population initialization.
- Oppositional-based approach also ensures mature convergence and enhances convergence rate during the process of searching for prey.
- The exploitation and exploration phases of conventional WOA increase the validity of it over other state-of-the-art algorithms.
- Chaotic opposition based initialization approach is a recently published approach. Therefore we have implemented it in this research area and we have obtained better results with respect to other state-of-the-art algorithms for all simulation instances.

Table 9 Optimal parameters achieved by COWOA and other meta-heuristic algorithms for simulation instance5

Parameter	Actual value	Estimated value				
		BA[22]	PSO[40]	WOA	COWOA	GA[21]
a_0	0.1084	0.4431	0.2484	0.1091	0.0396	0.5083
a_1	0.5419	0.7004	0.3789	0.3724	0.4239	0.7449
a_2	1.0837	1.0002	1.6960	0.5756	0.5689	1.0303
a_3	1.0837	0.9737	1.4109	0.0119	0.0920	1.0714
a_4	0.5419	0.8856	0.8467	0.0001	0.0001	0.7067
a_5	0.1084	0.2998	0.2684	0.0007	0.0068	0.3578
b_1	−0.9853	−0.8019	−1.0628	−0.0359	−0.0277	−0.6080
b_2	−0.9738	−1.2101	−0.7275	−0.0036	−0.0798	−0.9316
b_3	−0.3864	−0.4976	−0.4842	−0.0002	−0.0961	−0.3451
b_4	−0.1112	−0.3405	−0.3291	−0.0003	−0.0048	−0.3382
b_5	−0.0113	−0.0087	−0.2238	−0.0003	−0.0078	−0.1848

Table 10 Statistical analysis of COWOA and other meta-heuristic algorithms for simulation instance5

Fitness	BA[22]	PSO[40]	WOA	COWOA	GA[21]
Best	1.8299E−02	1.6283E−02	1.5277E−02	1.1363E−02	1.333E−02
Worst	5.6719E−02	3.2287E−02	2.063E−01	1.8832E−01	6.417E−02
Mean	2.0038E−02	1.7142E−02	1.3614E−02	**1.1531E−02**	3.399E−02
Std	3.109E−03	2.098E−03	3.257E−03	**1.1394E−03**	1.481E−02

The bold values confirm the superiority of the result of our propoed COWOA approach

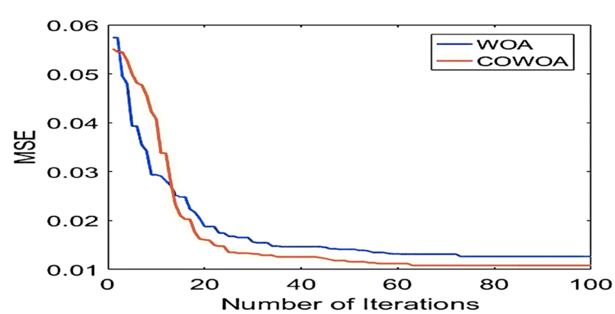

Fig. 9 MSE curves for simulation instance 5

Standard deviation is generally preferred over the best or mean value, as standard deviation directly relates to the consistency and reliability of an adaptive digital system. A high reliable system provides minimal standard deviation, whereas reliability is low for large standard deviation. It is clearly proved from Tables 2, 4, 6, 7, 9, and 12 that our proposed COWOA is much more reliable and consistent in terms of standard deviation from the other evolutionary optimization algorithms. For all the six test cases, COWOA is much more reliable than the other meta-heuristic algorithms.

It is observed from thorough simulation study that the suggested COWOA algorithm requires less iteration cycle for obtaining a global solution due to the concept of

Table 11 Optimal parameters achieved by COWOA and other meta-heuristic algorithms for simulation instance6

Parameter	Actual value	Estimated value	
		WOA	COWOA
a_0	0.1084	0.1069	0.1499
a_1	0.5419	0.3978	0.4792
a_2	1.0837	0.5828	0.0386
a_3	1.0837	0.0008	0.1037
a_4	0.5419	0.0077	0.2877
b_1	−0.9853	−0.0026	−0.3765
b_2	−0.9738	−0.0203	−0.0725
b_3	−0.3864	−0.0111	−0.0045
b_4	−0.0113	−0.0017	−0.0561

Table 12 Statistical analysis of COWOA and other meta-heuristic algorithms for simulation instance 6

Fitness	BA[22]	PSO[40]	WOA	COWOA	GA[21]
Best	6.819E−02	2.471E−02	1.2199E−02	1.016E−02	8.459E−02
Worst	8.9321E−01	4.3833E−01	1.8834E−01	1.7324E−01	290,488.5142
Mean	4.8739E−02	2.0561E−02	1.2955E−02	**1.077E−02**	32,386.62672
Std	6.321E−03	3.684E−03	2.312E−03	**2.140E−03**	96,788.75683

The bold values confirm the superiority of the result of our propoed COWOA approach

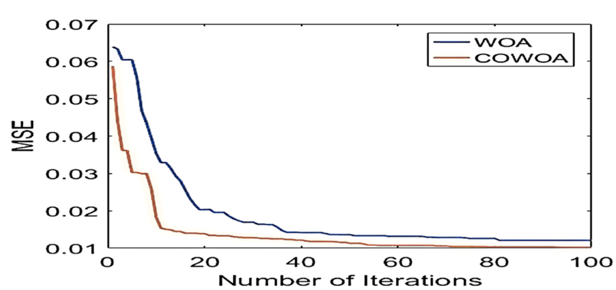

Fig. 10 MSE curves for simulation instance 6

opposition-based search technique within a given search space and also, it allows to adjust the convergence rate as desired by tuning a special parameter, called chaos control parameter. We have used examples in a systematic manner with the same and reduced order models. The results of our proposed COWOA algorithm have been executed before tabulation for 30 different times and compared with other meta-heuristic algorithms proposed by other researchers and clearly, COWOA shows better results than the other optimization algorithms like PSO, BA, WOA, GA, CIHS, CPSO-DE, etc. Also the overall computation time and time for convergence are significantly less than the others. Therefore, improvements in WOA that have been shown in our work make IIR system identification comparatively simpler, and the system designed will be statistically robust.

Conclusion

In this paper, we have suggested a chaotic oppositional planted approach which is processed before the start of the conventional WOA to enhance the convergence speed and to expand the perfection of algorithm's exploration and exploitation potentiality of the standard WOA using a more accurate and specific initialization process. The algorithm has some added advantages, like it is easy to recognize and transparent to realize, hence it can be adopted for a broad diversity of study in optimization fields. To ensure distinct characteristics within the population, OBL and chaotic concepts are simultaneously integrated in the individual search agent in each iteration. The observation performance for parameter identification is realized using the COWOA and the other four evolutionary optimization techniques, including the standard WOA, and the simulation outcomes apparently established that the COWOA indicates a greater identification achievement in forms of convergence momentum, certainty and stability within a set of statistical groundwork. It has also been observed from the comparison that the proposed COWOA has the ability to converge to a better quality solution with superior computational efficiency to find the optimal sets of adaptive IIR plant parameters for both the same order and reduced order models. Furthermore, less standard deviation achieved by COWOA in all six instants confirms the consistency towards the global solution which makes the digital IIR system identification more reliable and robust. From the MSE curves for different simulation instances, it is proved that our recommended approach for adaptive IIR filtering is capable of finding a maximum explanation in complex exploration area than conventional WOA.

Abbreviations

IIR	Infinite impulse response
FIR	Finite impulse response
MSE	Mean square error
RMSE	Root mean square error
PSO	Particle swarm optimization
GSA	Gravitational search algorithm
BA	Bat algorithm
OBL	Opposition based learning
WOA	Whale optimization algorithm
COWOA	Chaotic opposition-based whale optimization algorithm
RGA	Real coded genetic algorithm
CIHS	Chaotic improved harmony search
CPSO-DE	Cellular particle swarm optimization–differential evolution

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Author contributions
All the authors listed on the title page have contributed significantly to the work, have read the manuscript, attest to the validity and legitimacy of the data and its interpretation and agree to its submission. SD carried out the proposed architecture, participated in the preparing of tables, figures and simulation results and drafted the manuscript. PKR carried out the abstract, designed the algorithm and participated in the literature survey. AS described the conclusion section, performed the statistical analysis and participated in its design and coordination. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing Interests

The authors declare that they have no competing interests associated with this work.

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References

1. Litwin L (2000) FIR and IIR digital filters. IEEE Pot 19:28–31. https://doi.org/10.1109/45.877863
2. Saha SK, Kar R, Mandal D, Ghoshal S (2013) Optimal stable IIR low pass filter design using modified firefly algorithm. Spr SEMCCO Int Pub Switzerland 8297:98–109. https://doi.org/10.1007/978-3-319-03753-0_10
3. Proakis JG, Manolakis DG (2013) Digital signal processing: principles, algorithms and applications. Pearson Education, Singapore
4. Shenoi BA (2006) Introduction to Digital Signal Processing and Filter Design. Wiley-Interscience, Hoboken
5. Sidhu DS, Dhillon JS, Kaur D (2015) Design of digital IIR filter with conflicting objectives using hybrid gravitational search algorithm. Math Prob Engg Art 2015. https://doi.org/10.1155/2015/282809.
6. Tsai CW, Huang CH, Lin CL (2009) Structure-specified IIR filter and control design using real structured genetic algorithm. Appl Soft Com 9:1285–1295. https://doi.org/10.1016/j.asoc.2009.04.001
7. Antoniou A (2006) Digital signal processing: signals, systems and filters. McGraw Hill, USA
8. Kalinli A, Karaboga N (2005) A new method for adaptive IIR filter design based on Tabu search algorithm. Int J Electr Commun (AEÜ) 59:111–117. https://doi.org/10.1016/j.aeue.2004.11.003
9. Chung HC, Liang J (2004) Digital image processing for non-linear system identification. Int J Non-Linear Mech 39:691–707. https://doi.org/10.1016/S0020-7462(03)00021-0
10. Albaghdadi M, Briley B, Evens M (2006) Event storm detection and identification in communication systems. Rel Eng Syst Saf 91:602–613. https://doi.org/10.1016/j.ress.2005.05.001
11. Zhou X, Yang C, Gui W (2012) Nonlinear system identification and control using state transition algorithm. Appl Math Comput 226:169–179. https://doi.org/10.1016/j.amc.2013.09.055
12. Pai P, Nguyen BA, Sundaresan M (2013) Nonlinearity identification by time-domain-only signal processing. Int J Non-Lin Mech 54:85–98. https://doi.org/10.1016/j.ijnonlinmec.2013.04.002
13. Wang Y, Li B, Chen Y (2011) Digital IIR filter design using multi-objective optimization evolutionary algorithm. Appl Soft Comput 11:1851–1857. https://doi.org/10.1016/j.asoc.2010.05.034
14. Karaboga N, Centinkaya MB (2011) A novel and efficient algorithm for adaptive filtering: artificial bee colony algorithm. Turk J Elec Eng Comput Sci 19:175–190. https://doi.org/10.3906/elk-0912-344
15. Yao L, Sethares WA (1994) Nonlinear parameter estimation via the genetic algorithm. IEEE Tran Sig Pro 42:927–935. https://doi.org/10.1109/78.285655
16. Karaboga N (2009) A new design method based on artificial bee colony algorithm for digital IIR filters. J Frankl Inst 346:328–348. https://doi.org/10.1016/j.jfranklin.2008.11.003
17. Krusienski DJ, Jenkins WK (2004) Particle swarm optimization for adaptive IIR filter structures. IEEE Cong Evol Comp 1:965–970. https://doi.org/10.1109/CEC.2004.1330966
18. Chen S, Luk BL (2010) Digital IIR filter design using particle swarm optimization. Int J Mod Iden Cont 9:327–335. https://doi.org/10.1504/IJMIC.2010.033208
19. Dai C, Chen W, Zhu Y (2010) Seeker Optimization Algorithm for Digital IIR Filter Design. IEEE Trans Ind Electr 57:1710–1718. https://doi.org/10.1109/TIE.2009.2031194
20. Rashedi E, Pour HN, Saryazdi S, (2011) Filter modeling using gravitational search algorithm. Eng Appl Artif Intell 24:117–122. https://doi.org/10.1016/j.engappai.2010.05.007
21. Panda G, Pradhan PM, Majhi B (2011) IIR system identification using cat swarm optimization. Exp Syst Appl 38:12671–12683. https://doi.org/10.1016/j.eswa.2011.04.054
22. Saha SK, Kar R, Mandal D, Ghoshal SP (2013) A new design method using opposition-based BAT algorithm for IIR system identification problem. Int J Biol-Inst Comput 5(2):99–132. https://doi.org/10.1504/IJBIC.2013.053508
23. Ashok A, Singh S (2016) Flower pollination algorithm approach towards IIR system identification. Int J Artif Intell Appl Sm Dev 4:1–8. https://doi.org/10.14257/ijaiasd.2016.4.2.01
24. Upadhyay P, Kar R, Mandal D, Ghoshal SP (2016) A new design method based on firefly algorithm for IIR system identification problem. J King Saud Univ Eng Sci 28:174–198. https://doi.org/10.1016/j.jksues.2014.03.001.
25. Zhang S, Zhou Y (2018) Grey wolf optimizer with ranking-based mutation operator for IIR model identification. Chin J Elect 27:1071–1079. https://doi.org/10.1049/cje.2018.06.008
26. Humaidi AJ, Ibraheem IK, Ajel AR (2019) A novel adaptive LMS algorithm with genetic search capabilities for system identification of adaptive FIR and IIR filters. Info 10:176. https://doi.org/10.3390/info10050176
27. Durmus B, Yavuz G, Aydin D (2019) Adaptive IIR filter design using self-adaptive search equation based artificial bee colony algorithm. Turk J Electr Eng Comput Sci 27:4797–4817. https://doi.org/10.3906/elk-1809-83
28. Singh S, Asho A, Kumar M, Rawat TK (2019) Adaptive infinite impulse response system identification using teacher learner based optimization algorithm. Appl Intell 49:1785–1802. https://doi.org/10.1007/s10489-018-1354-4
29. Chang WD (2018) A Modified PSO Algorithm for IIR Digital Filter Modeling. J Circ Syst Comput 27:1. https://doi.org/10.1142/S0218126618500731
30. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Soft 95:51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008

31. Mousavi Y, Alfi A, Kucukdemiral IB (2020) Enhanced fractional chaotic whale optimization algorithm for parameter identification of isolated wind-diesel power systems. IEEE Access 8:140862–140875. https://doi.org/10.1109/ACCESS.2020.3012686
32. Chen H, Li W, Yang X (2020) A whale optimization algorithm with chaos mechanism based on quasi-opposition for global optimization problems. Exp Sys Appl 158:1. https://doi.org/10.1016/j.eswa.2020.113612
33. Luo Q, Ling Y, Zhou Y (2019) Modified whale optimization algorithm for infinitive impulse response system identification. Arab J Sci Eng 3:1. https://doi.org/10.1007/s13369-019-04093-1
34. Yang D, Li G, Cheng G (2007) On the efficiency of chaos optimization algorithms for global optimization. Chaos Solids Fract. 34:1366–1375. https://doi.org/10.1016/j.chaos.2006.04.057
35. Oliva D, Aziz M, Hassanien A (2017) Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm. Appl Energy 200:141–154. https://doi.org/10.1016/j.apenergy.2017.05.029
36. Gandomi AH, Yang XS (2014) Chaotic bat algorithm. J Comp Sci 5:224–232. https://doi.org/10.1016/j.jocs.2013.10.002
37. Rahnamayan S, Tizhoosh HR, Salama MA (2008) Opposition-Based Differential Evolution. IEEE Trans Evol Comput 12:64–79. https://doi.org/10.1109/TEVC.2007.894200
38. Roy PK, Paul C, Sultana S (2014) Oppositional teaching learning based optimization approach for combined heat and power dispatch. Electr Power Eng Syst 57:392–403. https://doi.org/10.1016/j.ijepes.2013.12.006
39. Sundaram A (2020) Multi-objective multi-verse optimization algorithm to solve combined economic, heat and power emission dispatch problems. Appl Soft Comput 91:106–195. https://doi.org/10.1016/j.asoc.2020.106195
40. Zou DX, Deb S, Wang GG (2016) Solving IIR system identification by a variant of particle swarm optimization. Neural Comput Appl 30:1–14. https://doi.org/10.1007/s00521-016-2338-0
41. Saha SK, Kar R, Mandal D, Ghoshal SP (2014) Gravitation search algorithm : application to the optimal IIR filter design. J King Saud Univ- Eng Soc 26:69–81. https://doi.org/10.1016/j.jksues.2012.12.003
42. Yang XS (2010) A new meta-heuristic bat inspired algorithm. Comput Knowl Technol 284:65–74. https://doi.org/10.1007/978-3-642-12538-6_6
43. Shafaati M, Mojallali H (2018) IIR filter optimization using improved chaotic harmony search algorithm. J Con Mea Elect Comp & Comm 59:331–339. https://doi.org/10.1080/00051144.2018.1541643
44. Upadhyay P, Kar R, Mandal D, Ghoshal SP (2014) Craziness based particle swarm optimization algorithm for IIR system identification problem. AEU Int J Electr Commun 68:369–378. https://doi.org/10.1016/j.aeue.2013.10.003
45. Eulogio PL, Mora JT, Romero NH, Mari JM (2017) A new design method for adaptive IIR system identification using hybrid CPSO and DE. Int J Nonlin Dyn Ch Eng Syst 55:1. https://doi.org/10.1007/s11071-017-3383-7.

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