Predator Prey Optimization Method For The Design Of IIR Filter

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Abstract :-The paper develops innovative methodology for the robust and stable design of digital infinite impulse response (IIR) filters using predator-prey optimization (PPO) method. Predator-prey optimization is undertaken as a global search technique and exploratory search is exploited as a local search technique. Being a stochastic optimization procedure, PPO technique, avoids local stagnation as preys play the role of diversification in the search of optimum solution due to the fear of predator(s). Exploratory search aims to fine tune the solution locally in promising search area. The proposed PPO method enhances the capability to explore and exploit the search space locally as well globally to obtain the optimal filter design parameters. A multivariable optimization is employed as the design criterion to obtain the optimal stable IIR filter that satisfies the different performance requirements like minimizing the magnitude approximation error and minimizing the ripple magnitude. The proposed method is effectively applied to design of low-pass, high-pass, band-pass, and band-stop digital IIR filters being multivariable optimization problems. The computational experiments show that the proposed PPO method is superior or at least comparable to other algorithms and can be efficiently applied for higher order filter design.

Key Words :-Digital IIR filters, Predator Prey Optimization, Exploratory search algorithm, Multi parameter optimization.

1 Introduction

A frequency selective circuit that allows a certain band of frequency to pass while attenuating the other frequencies is called a filter. Generally, filters are classified into two categories; (i) analog filters and (ii) digital filters. The digital filters can be implemented in hardware or through software and are capable to process both real-time and on-line (recorded) signals. Nowadays, digital filters can be used to perform many filtering tasks, which previously were performed almost exclusively by analog filters and are replacing the traditional role of analog filters in many applications. Image processing, speech synthesis, secure communication, radar processing and biomedical etc are some of the areas where digital filters are useful.

Digital infinite impulse response (IIR) filter design principally follows two techniques: transformation technique and optimization technique. In the transformation technique, analog IIR filter is designed initially and then it is transferred to digital IIR filter. Butterworth, Chebyshev and Elliptic function, have been developed using transformation techniques [10]. Optimization methods have been applied whereby magnitude error, and ripple magnitudes (tolerances) of both pass-band and stop-band are used to measure performance for the design of digital IIR filters. The design of IIR digital filter has been discussed by Jiang *et.al* [37] having stability constraint and employs an iterative second-order cone programming method. The simultaneous design in magnitude and group delay has been discussed by Lightener *et,al*.[3]. To guarantee the stability of IIR digital filters, a stability constraint with a prescribed pole radius has been derived from the argument principle of complex analysis. For designing problem of IIR filter in a convex form, the semi-definite programming relaxation technique [38] has been used. Being a sequential design procedure, the algorithm finds a feasible solution within a set of relaxed constraints. However, non-linear and multimodal nature of error surface of IIR filters, conventional gradient-based design may easily get stuck in the local minima of error surface.

To overcome the draw backs of gradient methods, various researchers applied modern heuristics optimization algorithms such as genetic algorithms [4,6,8,9,11,13,17,18], particle swarm optimization (PSO) [19], seeker- optimization- algorithm -based evolutionary method [25], simulated annealing (SA) [12], tabu search [24], ant colony optimization [20], immune algorithm [27] etc for the design of digital filters.

Evolutionary algorithms (EAs) are based on the mechanics of natural selection and genetics. Genetic algorithms are one example of EAs. The optimization methods based on genetic algorithms are only capable of searching multidimensional and multimodal spaces. These are also able to optimize complex and discontinuous functions [8]. The digital IIR filter can be structured such as cascade, parallel, or lattice. The low-pass, high-pass, band-pass, and band-stop filters can be independently designed. To design the digital IIR filters genetic algorithm has been applied by Tang *et al.*[8]. The genetic methods are normally compromised because of their very slow convergence. When the number of the parameters is large, these may trap in the local optima of objective function and there are numerous local optima [7]**.** The hybrid Taguchi genetic algorithm has been applied by Tsai *et al.* [26] for design of optimal IIR filters. With hybrid Taguchi genetic algorithm approach, the combination of the traditional genetic algorithms, which has a powerful global exploration capability, is applied with the Taguchi method. Hence, it is necessary for further developing an efficient heuristic algorithm so as to design the optimal digital IIR filters.

Tsai *et al.* [27] has purposed an approach by integrating the immune algorithm and the Taguchi method named as Taguchi-immune algorithm (TIA). Yu *et.al.* [31] have proposed cooperative co-evolutionary genetic algorithm for digital IIR filter design. For finding the lowest filter order, the magnitude and the phase response has been considered. The structure and the coefficients of the digital IIR filter have been coded separately. For keeping the diversity, the simulated annealing has been used for the coefficient species, but to arrive at global minima [12], it may require too many function evaluations. The seeker-optimization-algorithm can be implemented. It is good at local convergence. It might often require too many cost function evaluations for the global minima [25]. In the literature, there are various methods with which the optimization problem under different conditions can be addressed. Based on the type of the search space and the objective function different optimization methods are classified. Due to the time-consuming computer simulation or expensive physical experiments, the evaluation of candidate solutions could be computationally and/or financially expensive in IIR filter design problems. Therefore, a method is of great practical interest if it is able to produce reasonably good solutions within a given (often very tight) budget on computational cost/time.

Kennedy and Eberhart [5] have originally introduced the particle swarm optimization which is a global search technique. The PSO has simple concept. It is easy to implement and has fast computation. It has robust search ability. In PSO, the social evolvement knowledge is simulated through, probing the optimum by evolving the population which may include candidate solutions. In comparison to other EAs, PSO has shown incomparable advantages in searching speed and precision [23]. Irrespective of several advantages of PSO, it has some shortcomings. The convergence behavior of PSO depends upon its parameters. In case the PSO parameters are wrongly chosen, this may result in divergent particle trajectories which cause trapping into local minimum value [34]. When PSO is applied to high-dimensional optimization problems, the premature convergence problem may suffer which results in a low optimization precision or sometimes even failure [35]. For improving the performance of PSO, various attempts have been made by researchers either through mathematical analysis or in improving PSO algorithm [16,22,28,29,41,42]. From the individual particle's point of view the working of PSO has been explored by Clerc and Kennedy [16]. As concluded by Bergh and Engelbrecht [28], the PSO algorithm does not guarantee to converge to the global optimum by fixing the parameters. The stability of particle dynamics has been analyzed by Kadirkamanathan *et al.* [29] by using Lyapunov stability analysis and the concept of passive systems. On the basis of statistical interpretation, Chen and Jiang [40] have analyzed the behavior of PSO. This has been done on the basis of social model and then derived the upper and lower bounds of the expected particle norm. The behavior of particles in the PSO has been investigated by Gao and Xu [35] using a Monte Carlo method. The researchers also aim to improve the PSO algorithm in various ways. These amelioration can be classified into five categories: (i) inertial weight varying strategy, (ii) parameter selection and convergence analysis [21] (iii) swarm topology structure (iv) discrete PSO (v) hybrid PSO combined with some evolutionary computation operators and other methods. All these proposals

usually involve changes, to the PSO to update equations, without changing the structure of the algorithm. On the basis of variation of particle swarm optimization, namely, quantum-behaved particle swarm optimization, the quantum-behaved particle swarm optimization with diversity-guided has been applied for the design of 2-D IIR digital filters by Sun *et.al*. [39].The particle swarm optimization performance may be influenced by premature convergence and stagnation problem [33]. Zhou *et al*. [42] have adopted the hill climbing moves on the idea of SA algorithm to guide the flying particles of PSO.

In the conventional PSO algorithm, the swarm would come together at a time and then it must be difficult for them to escape from the accumulation point. After that, the algorithm would lose its global search ability. For overcoming this deficiency of PSO, a predator-prey model has been developed by Silva *et al*. [14]. The motivation has mainly introduced diversity in the swarm position at any moment during the run of the algorithm, which does not depend on the level of convergence already achieved. Silva *et al*. [15] and Higashitani *et al*. [30] have developed the predator-prey optimization (PPO) method and applied on several benchmark problems and has compared with PSO method. They have concluded that PPO performed significantly better than the standard PSO while implanted on benchmark multimodal functions. Johnson *et al*. [36] has discussed the application of four variants of PSO to data clustering. He has concluded that predator-prey method is more beneficial to the clustering, as keeping the particles moving, is highly important, because a good position obtained now, may not be good shortly afterwards. Still, PPO has not been applied to constrained problems, to real systems, which are getting so much attention in these days. A detailed overview of the basic concepts of PSO and its variants was presented by Del *et al*. [32].

The intent of this paper is to propose a predator-prey optimization method for the design of IIR digital filters that randomly explores the search space globally as well locally. The values of the filter coefficients are optimized with the PPO to achieve magnitude error and ripple magnitude as objective functions for optimization problem. Constraints are taken care of by applying exterior penalty method. This paper is organized in five sections. Section 2 describes the IIR filter design problem statement. The underlying mechanism and details regarding the PPO algorithm for designing the optimal digital IIR filters is described in Section 3. The performance of the proposed PPO has been

evaluated and achieved results are compared with the design results by Tang *et al*. [8], Tsai *et al*. [26] and Tsai and Horng [27] for the LP, HP, BP, and BS filters in section 4. Finally, in section 5 the conclusions and discussions are outlined.

2   IIR Filter Design Problem

A digital filter design problem determines a set of filter coefficients which meet performance specifications. These performance specifications are (i) pass band width and its corresponding gain, (ii) width of the stop-band and attenuation, (iii) band edge frequencies, and (iv) tolerable peak ripple in the pass band and stop-band. The design of the IIR filter is mathematically stated by the following difference equation:

$$y(n) = \sum_{k=0}^{N} p_k x(n-k) - \sum_{j=1}^{M} q_j y(n-j) \tag{1}$$

where:-

p_k and q_j are the coefficient of the filter.

$x(n)$ and $y(n)$ are filter input and output, respectively.

N and M gives order of filter with $M \geq N$.

The transfer function of IIR filter is defined below:

$$H(z) = \frac{\sum_{k=0}^{N} p_k z^{-k}}{1 + \sum_{j=1}^{M} q_j z^{-j}} \tag{2}$$

The design of digital filter design problem involves evaluation of a set of filter coefficients, p_k and q_j which meet the performance indices. Several first- and second-order sections are cascaded together [7-8] for realizing IIR filters.

The cascaded transfer function of IIR filter is denoted by $H(\omega, x)$, involving the filter coefficients like, poles and zeros. Irrespective of the filter type, the structure of cascading type digital IIR filter, is stated as [4].

$$H(\omega, x) = x_1 \left(\prod_{i=1}^{N} \frac{1 + x_{2i} e^{-j\omega}}{1 + x_{2i+1} e^{-j\omega}} \right) \times \left(\prod_{k=1}^{M} \frac{1 + x_l e^{-j\omega} + r_{i+1} e^{-2j\omega}}{1 + x_{l+3} e^{-j\omega} + x_{l+4} e^{-2j\omega}} \right) \tag{3}$$

where:

$l = 2N + 4(k-1) + 2$ and vector $x = [x_1 \quad x_2 \quad ...x_S]^T$ denotes the filter coefficients of dimension S×1 with $S = 2N + 4M + 1$.

In the IIR filter, the coefficients are optimized such that the approximation error function for magnitude is to be minimized. The magnitude response is specified at K equally spaced discrete

frequency points in pass-band and stop-band. $e(x)$ denotes the absolute error and is defined as below:

$$e(x) = \sum_{i=0}^{K} \left\| H_d(\omega_i) - |H(\omega_i, x)| \right\| \qquad (4)$$

Desired magnitude response, $H_d(\omega_i)$ of IIR filter is given as:

$$H_d(\omega_i) = \begin{cases} 1, & ; for\ \omega_i \in passband \\ 0, & ; for\ \omega_i \in stopband \end{cases} \qquad (5)$$

The ripple magnitudes of pass-band and stop-band are given by $\delta_1(x)$ and $\delta_2(x)$, respectively [2]. Ripple magnitudes are defined as:

$$\delta_1(x) = \max_{\omega_i} \left\{ |H(\omega_i, x)| \right\} - \min_{\omega_i} \left\{ |H(\omega_i, x)| \right\}; \omega_i \in passband$$
$$\qquad (6)$$

and

$$\delta_2(x) = \max_{\omega_i} \left\{ |H(\omega_i, x)| \right\}; \omega_i \in stopband \qquad (7)$$

Stability constraints are included in the design of casual recursive filters, which are obtained by using the Jury method [1]. The multivariable constrained optimization problem is stated as below:

Minimize $f(x) = e(x)$ $\qquad (8)$

Subject to the stability constraints:-

$$1 + x_{2i+1} \geq 0 \ (i = 1, 2, \ldots, N) \qquad (9)$$
$$1 - x_{2i+1} \geq 0 \ (i = 1, 2, \ldots, N) \qquad (10)$$
$$1 - x_{l+3} \geq 0 \ (l = 2N + 4(k-1) + 2, k = 1, 2, \ldots, M) \qquad (11)$$
$$1 + x_{l+2} + x_{l+3} \geq 0 \ (l = 2N + 4(k-1) + 2, k = 1, 2, \ldots, M,) \qquad (12)$$
$$1 - x_{l+2} + x_{l+3} \geq 0 \ (l = 2N + 4(k-1) + 2, k = 1, 2, \ldots, N) \qquad (13)$$

Scalar constrained optimization problem is converted into unconstrained multivariable optimization problem using penalty method. Augmented function is defined as

$$A(x) = f(x) + r\left(P_{tem}\right) \qquad (14)$$

where

$$P_{tem} = \sum_{i=1}^{N} \left\langle 1 + x_{2i+1} \right\rangle^2 + \sum_{i=1}^{N} \left\langle 1 - x_{2i+1} \right\rangle^2 + \sum_{k=1}^{M} \left\langle 1 - x_{l+3} \right\rangle^2$$
$$+ \sum_{k=1}^{M} \left\langle 1 + x_{l+2} + x_{l+3} \right\rangle^2 + \sum_{k=1}^{M} \left\langle 1 - x_{l+2} + x_{l+3} \right\rangle^2$$

r is a penalty parameter having large value.

Bracket function for constraint given by Eq. (9) is stated below:-

$$\left\langle 1 + x_{2i+1} \right\rangle = \begin{cases} 1 + x_{2i+1} & ; if \left(1 + x_{2i+1} \right) < 0 \\ 0 & ; if \left(1 + x_{2i+1} \right) \geq 0 \end{cases} \qquad (15)$$

Bracket function for constraint given by Eq. (12) is stated below:-

$$\left\langle 1 + x_{l+2} + x_{l+3} \right\rangle = \begin{cases} 1 + x_{l+2} + x_{l+3} & if \left(1 + x_{l+2} + x_{l+3} \right) < 0 \\ 0 & if \ (1 + x_{l+2} + x_{l+3}) \geq 0 \end{cases} \qquad (16)$$

Similarly bracket functions for other constraints given by Eq. (10), Eq.(11) and Eq. (13) are undertaken.

3 Predator Prey Optimization for the Design of IIR Filter

The predator-prey optimization technique is based on particle swarm optimization (PSO) with additional predator effect. Particle swarm optimization is a population based search technique and utilizes swarm intelligence such as bird flocking, fish schooling. Particle changes its position with time based on its own experience and experience of neighboring particles. The position mechanism of the particle in the search space is updated by adding the velocity vector to its position vector [5]. In PPO model, predator population is included with swarm particles. Predators have a different dynamic behavior from swarm particles; they are attracted to the best individuals in the swarm, while the other particles are repelled by their presence. Prey particles always try to attain best suited position to avoid predator's attack. The probability fear *(pf)* controls the influence of predator on any individual particle of the swarm. Exploration and exploitation is balanced and maintained by controlling the strength and frequency of the interactions between predator and prey. In PPO model, predator plays the role of searching around global best in a concentrated manner, whereas preys explore on a solution space roughly escaping from predators, which helps to avoid premature convergence to local optima. In case the predator attacks the prey then an exponential term will also be included in velocity vector as given by Silva et al., [15]. Basic PPO algorithm is elaborated below.

Algorithm 1:-*Predator prey optimization*
1. Input data viz. maximum allowed movements, swarm size, maximum and minimum limit of velocity, maximum probability fear (pf) etc.
2. Randomly initialize the prey and predator positions being decision variables.
3. Randomly initialize the prey and predator velocities.
4. Compute augmented objective function.
5. Assign all prey positions as their local best position.
6. Compute global best position among local best position of prey. (10)
7. Update predator velocity and position.
8. Randomly generate the probability fear within (0, 1)
9. IF (probability fear > maximum probability fear) THEN
     Update prey velocity and position with predator affect
   ELSE
     Update prey velocity and position without predator affect
   ENDIF.

10. Compute augmented objective function for all prey population.
11. Update particles local best position of prey particles.
12. Perform exploratory move for the refinement of position of prey particles.
13. Global best position of prey particles based on fitness.
14. Check stopping criteria, if not met, repeat step 7.
15. Stop

3.1 Initialization of population position and velocity

The Initial positions of preys and predator are randomly initialized between upper and lower limits. Total population consists of N_P preys and a single predator. Prey and predator positions, x_{ik}^0 and x_{Pi}^0, respectively of IIR filter coefficients (decision variables) are randomly initialized within their respective upper and lower limits.

$$x_{ik}^0 = x_i^{min} + R_{ik}^1\left(x_i^{max} - x_i^{min}\right) \left(i=1,2,...,S; k=1,2,...,N_P\right) \quad (17)$$

$$x_{Pi}^0 = x_i^{min} + R_i^2\left(x_i^{max} - x_i^{min}\right) \left(i=1,2,...,S\right) \quad (18)$$

where x_i^{min} and x_i^{max} are representing the lower and upper limit of ith decision variables, respectively; R_i^1 and R_i^2 are uniform random numbers having value between 0 and 1.

Prey and predator velocities, V_{ik}^0 and V_{Pi}^0, respectively of decision variables are randomly initialized within their respective predefined limits.

$$V_{ik}^0 = V_i^{min} + R_{ik}^1\left(V_i^{max} - V_i^{min}\right)\left(i=1,2,...,S; k=1,2,...,N_P\right) \quad (19)$$

$$V_{Pi}^0 = V_{Pi}^{min} + R_i^2\left(V_{Pi}^{max} - V_{Pi}^{min}\right)\left(i=1,2,...,S\right) \quad (20)$$

where minimum and maximum prey velocities are set using the following relation

$$V_i^{min} = -\alpha\left(x_i^{max} - x_i^{min}\right)\left(i=1,2,...,S\right) \quad (21)$$

$$V_i^{max} = +\alpha\left(x_i^{max} - x_i^{min}\right)\left(i=1,2,...,S\right) \quad (22)$$

By varying value of α, minimum and maximum velocities for preys are obtained. α is less than 0.1.

3.2 Predator velocity and position evaluation

The predator velocity and position, representing decision variables, updates for $(t+1)^{th}$ movement/iteration are given below:

$$V_{Pi}^{t+1} = C_4\left(GPbest_i^t - P_{Pi}^t\right)\left(i=1,2,...,S\right) \quad (23)$$

$$x_{Pi}^{t+1} = x_{Pi}^t + V_{Pi}^{t+1}\left(i=1,2,...,S\right) \quad (24)$$

where $GPbest_i^t$ is global best prey position of ith variable; C_4 is the random number lies between 0 and upper limit.

The elements of predator position x_{Pi}, and corresponding velocity, V_{Pi} may violate its limit.

This violation is set by fixing their values either at lower or upper limits.

3.3 Prey velocity and position evaluation

The velocity and position of a prey particle representing variables updates for $(t+1)^{th}$ movement/iteration are given by:

$$V_{ik}^{t+1} = \begin{cases} wV_{ik}^t + C_1R_1\left(xbest_{ik}^t - x_{ik}^t\right) + C_2R_2\left(Gxbest_{ik}^t - x_{ik}^t\right) & ; P_f \leq P_f^{max} \\ wV_{ik}^t + C_1R_1\left(xbest_{ik}^t - x_{ik}^t\right) + C_2R_2\left(Gxbest_{ik}^t - x_{ik}^t\right) + C_3a\left(e^{-bek}\right) & ; P_f > P_f^{max} \end{cases}$$

$$\left(i=1,2,...,S; k=1,2,...,N_P\right) \quad (25)$$

$$x_{ik}^{t+1} = x_{ik}^t + c_{fc}V_{ik}^{t+1} \quad \left(i=1,2,...,S; k=1,2,...,N_P\right) \quad (26)$$

where C_1, and C_2 is the acceleration constant; R_1 and R_2 are uniform random numbers having value between 0 and 1; w is inertia weight; $xbest_{ik}^t$ is local best position of ith variable and k^{th} population; Constant 'a' provides the maximum amplitude of the predator effect over a prey and 'b' allows controlling the effect. C_3 is a random number in the range 0 and 1 and it influences the effect of predator on prey [22]. e_k is Euclidean distance between predator and prey position for k^{th} population given as:

$$e_k = \sqrt{\sum_{i=1}^{S}\left(x_{ik} - x_{Pi}\right)^2} \quad (27)$$

The inertia weight is calculated by adopting following relation and it shows the decreasing trend as the iteration progresses.

$$w = f_w\left[w^{max} - \left(w^{max} - w^{min}\right)\left(t/t_{max}\right)\right]$$

Randomness is maintained by applying chaotic sequence which is given below

$$f_w = 4f_w\left(1 - f_w\right) \qquad \text{where } f_w \notin \left[0, 0.25, 0.50, 0.75, 1\right]$$

C_{fc} is the constrict factor and is defined by the following equation:

$$C_{fc} = \begin{cases} \left|2 - \phi - \sqrt{\phi^2 - 4\phi}\right| & if\ \phi \geq 4 \\ 1 & if\ \phi < 4 \end{cases}$$

The elements of prey positions x_{ik}^t, and velocities V_{ik}^t may violate their limits. This violation is set by updating their values on violation either at lower or upper limits.

$$V_{ik}^t = \begin{cases} V_{ik}^t + R_3V_i^{max} & ; if\ V_{iki}^t < V_i^{min} \\ V_{ik}^t - R_3V_i^{max} & ; if\ V_{ik}^t > V_i^{max} \\ V_{ik}^t & ; no\ violation of\ limits \end{cases} \quad (28)$$

where R_3 is any uniform random number between 0 and 1. The process is repeated till the satisfying the limits. Similarly, predator velocity limits are adjusted.

3.4 Exploratory Move

In the exploratory move, the current point is perturbed in positive and negative directions along

each variable one at a time and the best point is recorded. The current point is updated to the best point at the end of each design variable perturbation may either be directed or random. If the point found at the end of all filter coefficient perturbations is different from the original point, the exploratory move is a success; otherwise, the exploratory move is a failure. In any case, the best point is considered to be the outcome of the exploratory move. The starting point obtained with the help of random initialization is explored iteratively and filter coefficient x_i is initialized as follows:

$$x_i^n = x_i^o \pm \Delta_i u_i^j \quad (i = 1, 2, ..., S; j = 1, 2, ..., S) \qquad (29)$$

where

$$u_i^j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \qquad (30)$$

S denotes number of variables.

The objective function denoted by $A(x_i^n)$ is calculated as follows

$$x_i^n = \begin{cases} x_i^o + \Delta_i u_i & ; A(x_i^o + \Delta_i u_i) < A(x_i^o) \\ x_i^o - \Delta_i u_i & ; A(x_i^o - \Delta_i u_i) < A(x_i^o) \\ x_i^o & ; otherwise \end{cases} \qquad (31)$$

where $(i = 1, 2, ..., S)$ and Δ_i is random for global search and fixed for local search.

The process is repeated till all the filter coefficients are explored and overall minimum is selected as new starting point for next iteration. The stepwise algorithm to explore filter coefficients is outlined below.

Algorithm 2:- *Exploratory move*
1. Select small change, Δ_i, and x_i^o and compute $f(x_i^o)$
2. Initialize iteration counter, IT=0
3. Increment the counter, IT=IT+1
4. IF $(IP > IP^{max})$ GO TO 12
5. Initialize filter coefficient counter j=0
6. Increment filter coefficient counter, j=j+1
7. Find u_i^j using Eq. (30)
8. Evaluate performance function, $A(x_i^o + \Delta_i u_i^j)$ and $A(x_i^o - \Delta_i u_i^j)$
9. Select x_i^n using Eq. (31) and $A(x_i^n)$
10. IF $(j \leq S)$ GO TO 6 and repeat.
11. IF $A(x_i^n) < A(x_i^o)$
    THEN GO TO 5
    ELSE $\Delta_i = (\Delta_i / 1.618)$ and GOTO 3 and repeat.
12. STOP

4 IIR filter design and comparisons
The design of cascaded digital IIR filter has been implemented. The filter coefficients have been

evaluated by applying PPO method. Low pass (LP), high pass (HP), band pass (BP) and band stop (BS) filters have been considered for the design. Design conditions for these filters are given in Table 1.

Table 1
Design conditions on LP, HP, BP and BS filters.

Filter type	Pass-band	Stop-band	$|H(\omega, x)|$
Low-Pass(LP)	$0 \leq \omega \leq 0.2\pi$	$0.3\pi \leq \omega \leq \pi$	1
High-Pass(HP)	$0.8\pi \leq \omega \leq \pi$	$0 \leq \omega \leq 0.7\pi$	1
Band-Pass(BP)	$0.4\pi \leq \omega \leq 0.6\pi$	$0 \leq \omega \leq 0.25\pi$ $0.75 \leq \omega \leq \pi$	1
Band-Stop(BS)	$0 \leq \omega \leq 0.25\pi$ $0.75 \leq \omega \leq \pi$	$0.4\pi \leq \omega \leq 0.6\pi$	1

To design digital IIR filter, 200 equally spaced points are set within the frequency domain $[0, \pi]$, such that the number of discrete frequency points in Eq. (4), comes out 182 for the LP and HP filters, and 143 for the BP and BS filters along with prescribed pass-band and stop-band frequency range is given in Table 1.

Here, in PPO approach, for the design of LP, HP, BP and BS digital IIR filters, the population has been taken as 30, maximum number of movements of swarm has been taken as 50. The penalty parameter used in Eq.(14) is chosen as 75. The value of maximum amplitude of the predator effect over a prey, 'a' and controlling the effect, 'b' have been considered as $0.0008 \times x_i^{max}$ and $0.008/x_i^{max}$, respectively. The maximum and minimum inertia weight has been taken as 0.9 and 0.3, respectively. The value of acceleration constant C_1 and C_2 used in Eq.(25) has been determined as $C_1 = \beta\phi$ and $C_2 = (1 - \beta)\phi$ so that $C_1 + C_2 = \phi$.

The value of ϕ has been taken as 3.0. β gives the social behavior or cognitive behavior effect in percentage and is taken as 50%. The P_f and P_f^{max} used in Eq.(25) has been taken as 0.015 and 0.05, respectively. α is taken as 0.0275 to find the minimum and maximum velocity, respectively. For pattern movement iterations, IP^{max} are taken as 10. Chaotic sequence is initiated with a value 0.59

The IIR filter models designed by the PPO approach for LP, HP, BP and BS are given below in Eq.(32), Eq.(33), Eq.(34) and Eq.(35), respectively.

$$H_{LP}(z) = 0.37740 \frac{(z + 0.862602)(z^2 - 0.305099z + 1.027876)}{(z - 0.655841)(z^2 - 1.380727z + 0.729233)}$$

$$(32)$$

$$H_{HP}(z)=0.033929\times\left(\frac{z-1.256915}{z+0.649485}\right)$$
$$\times\left(\frac{z^2+0.370169z+1.042865}{z^2+1.365590z+0.727653}\right) \quad (33)$$

$$H_{BP}(z)=0.029935\times\left(\frac{z^2-0.208605z-1.088681}{z^2-0.651338z+0.771629}\right)$$
$$\times\left(\frac{z^2+0.224494z-0.743448}{z^2+0.006754z+0.539080}\right)\times\left(\frac{z^2-0.059816z-0.974508}{z^2+0.641817z+0.767235}\right)$$
$$(34)$$

$$H_{BS}(z)=0.412417\times\left(\frac{(z^2+0.331478z+1.000991)}{(z^2-0.814150z+0.505172)}\right)$$
$$\times\left(\frac{z^2-0.337257z+0.989966}{z^2+0.810263z+0.506139}\right) \quad (35)$$

In predator-prey optimization, the magnitude error is considered along with the ripple magnitudes of pass-band and ripple magnitude of stop-band. The computational results obtained by the predator prey optimization for LP filter is given in Table 2.

Table 2
Design Results For LP Filter

Method	Magnitude Error	Pass-band performance	Stop-band performance
PPO	3.6611	$0.9178\leq\left|H(e^{j\omega})\right|\leq1.000$ (0.0998)	$\left|H(e^{j\omega})\right|\leq0.1611$ (0.1611)
HGA [8]	4.3395	$0.8870\leq\left|H(e^{j\omega})\right|\leq1.000$ (0.1139)	$\left|H(e^{j\omega})\right|\leq0.1802$ (0.1802)
HTGA [26]	4.2511	$0.90004\leq\left|H(e^{j\omega})\right|\leq1.000$ (0.0996)	$\left|H(e^{j\omega})\right|\leq0.1247$ (0.1247)
TIA [27]	3.8157	$0.8914\leq\left|H(e^{j\omega})\right|\leq1.000$ (0.1086)	$\left|H(e^{j\omega})\right|\leq0.1638$ (0.1638)
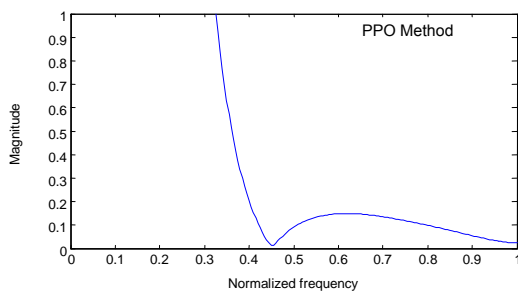
Fig 1 Frequency response of LP filter using PPO
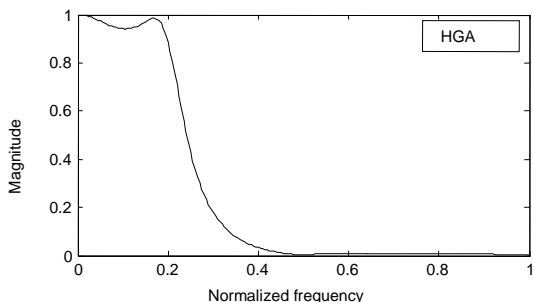
Fig 2 Frequency response of LP filter using HGA [8].

The frequency response using PPO is shown in Fig. 1 for LP filter. The frequency responses obtained by Tang *et al.*[8] Tsai et al.[26] and Tsai and Horng [27], are depicted in Fig. 2, Fig. 3 and Fig. 4, respectively for LP filter. The pole zero plot of LP filter for PPO is given in Fig 5.
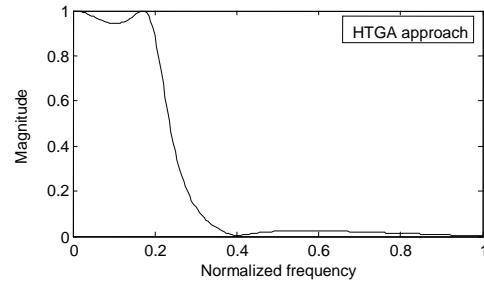

Fig 3 Frequency response of LP filter using HTGA [26]
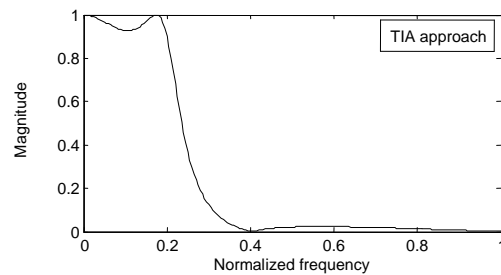

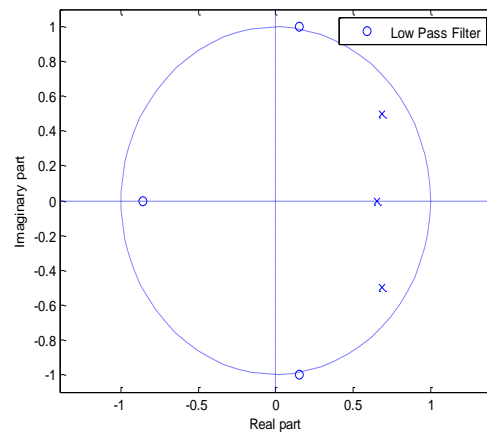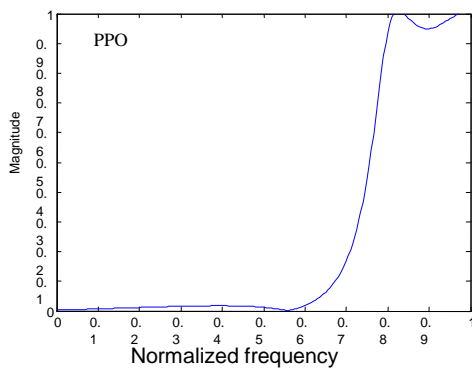Fig 4 Frequency response of LP filter using TIA [27].

Fig 5 Pole-Zero plot of Low Pass filter

The computational results obtained by the predator prey optimization for HP filter is given in Table 3. The frequency response using PPO is shown in Fig. 6 for HP filter.

The frequency responses obtained by Tang *et al.*[8] Tsai et al.[26] and Tsai and Horng [27], are depicted in Fig. 7, Fig. 8 and Fig. 9, respectively for HP filter. The pole-zero plot using PPO is shown in Fig. 10 for HP filter.

Table 3
Design Results For HP Filter

Method	Magnitude Error	Pass-band performance	Stop-band performance
PPO	3.9332	$0.9401 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.0717)	$\left\| H(e^{j\omega}) \right\| \leq 0.1692$ (0.1692)
HGA [8]	14.5078	$0.9224 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.0779)	$\left\| H(e^{j\omega}) \right\| \leq 0.1819$ (0.1819)
HTGA [26]	4.8372	$0.9460 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.0540)	$\left\| H(e^{j\omega}) \right\| \leq 0.1457$ (0.1457)
TIA [27]	4.1819	$0.9229 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.0771)	$\left\| H(e^{j\omega}) \right\| \leq 0.1424$ (0.1424)

Fig 6 Frequency Response of HP filter using PPO
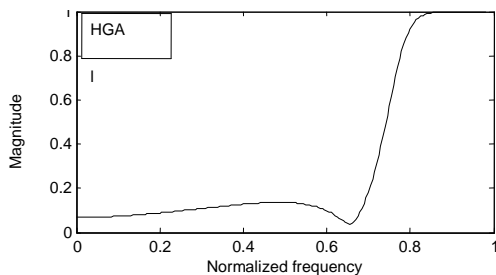
Fig 7 Frequency Response of HP filter using HGA [8]
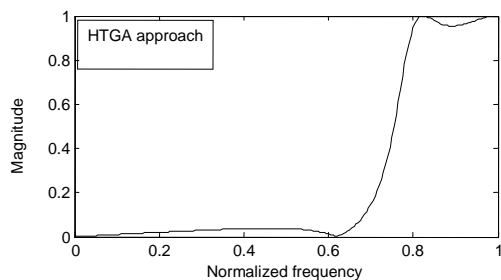
Fig 8 Frequency Response of HP filter using HTGA [26]

The computational result obtained by the predator prey optimization for BP filter is given in Table 4. The frequency response obtained by PPO for BP filter is shown in Fig. 11. The frequency responses obtained by Tang *et al.*[8] Tsai et al.[26] and Tsai and Horng [27], are depicted in Fig. 12, Fig. 13 and

Fig.14, respectively for BP filter. The pole-zero plot obtained by PPO is shown in Fig. 15 for BP filter.
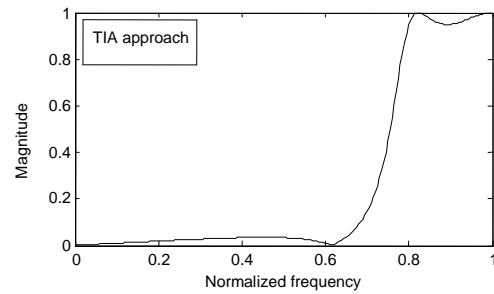

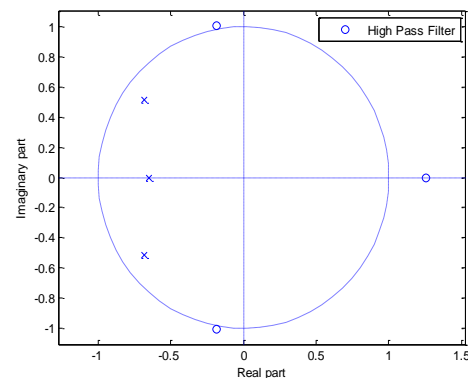Fig 9 Frequency Response of HP filter using TIA [27]

Fig 10 Pole Zero plot of High Pass filter

TABLE 4
Design Results For BP Filter

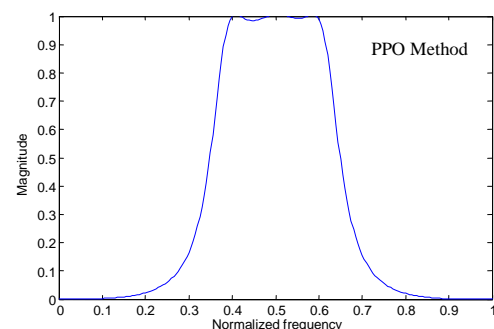| Method	Magnitude Error	Pass-band performance	Stop-band performance
PPO	1.4212	$0.9851 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.0203)	$\left\| H(e^{j\omega}) \right\| \leq 0.0603$ (0.0603)
HGA. [8]	5.2165	$0.8956 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.1044)	$\left\| H(e^{j\omega}) \right\| \leq 0.1772$ (0.1772)
HTGA [26]	1.9418	$0.9760 \leq \left\| H(e^{j\omega}) \right\| \leq 1.0000$ (0.0234)	$\left\| H(e^{j\omega}) \right\| \leq 0.0711$ (0.0711)
TIA [27]	1.5204	$0.9681 \leq \left\| H(e^{j\omega}) \right\| \leq 1.000$ (0.0319)	$\left\| H(e^{j\omega}) \right\| \leq 0.0679$ (0.0679)

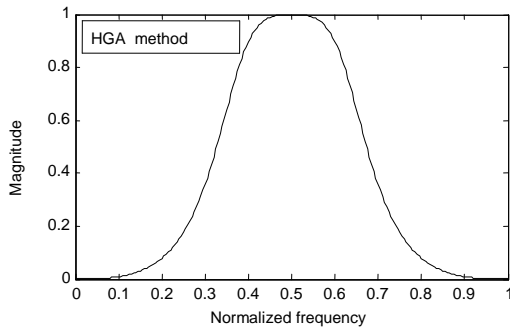Fig 11 Frequency response of BP filter using PPO

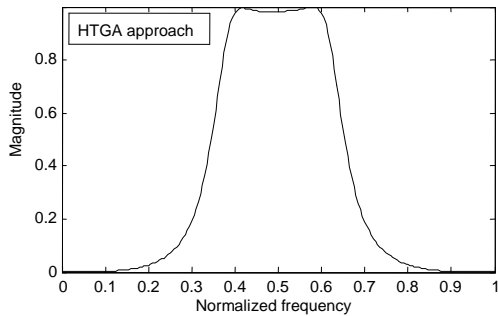Fig 12 Frequency response of BP filter using HGA [8]

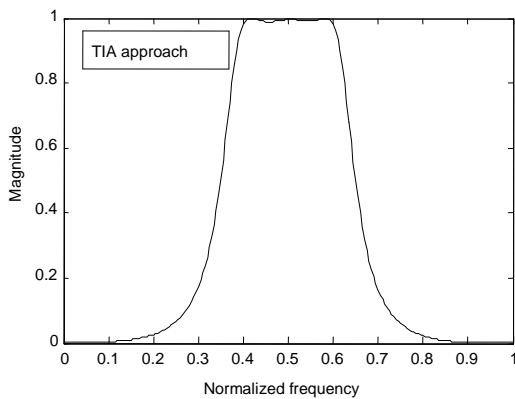Fig 13 Frequency response of BP filter using HTGA [26]

Fig 14 Frequency response of BP filter using TIA[27]
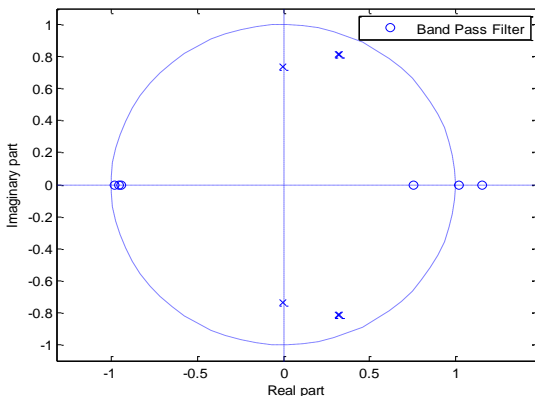

Fig 15 Pole Zero Plot of BP filter

The computational results obtained by the predator prey optimization for BS filter is given in Table 5. The frequency response obtained by PPO is shown in Fig. 16 for BS filter. The frequency responses obtained by Tang *et al.*[8] Tsai et al.[26] and Tsai and Horng [27], are depicted in Fig. 17, Fig. 18 and Fig 19, respectively for BS filter. Pole-zero plot is obtained by PPO is shown in Fig. 20 for BS filter.

TABLE 5
Design Results For BS Filter

Method	Magnitude Error	Pass-band performance	Stop-band performance
PPO	4.1160	$0.9560 \leq \left| H(e^{j\omega}) \right| \leq 1.0000$ (0.0437)	$\left| H(e^{j\omega}) \right| \leq 0.1170$ (0.1170)
HGA. [8]	6.6072	$0.8920 \leq \left| H(e^{j\omega}) \right| \leq 1.0000$ (0.1080)	$\left| H(e^{j\omega}) \right| \leq 0.1726$ (0.1726)
HTGA [26]	4.5504	$0.9563 \leq \left| H(e^{j\omega}) \right| \leq 1.0000$ (0.0437)	$\left| H(e^{j\omega}) \right| \leq 0.1013$ (0.1013)
TIA [27]	4.1275	$0.9560 \leq \left| H(e^{j\omega}) \right| \leq 1.0000$ (0.0440)	$\left| H(e^{j\omega}) \right| \leq 0.1171$ (0.1171)

For comparison purposes, the digital IIR filter lowest order has been set exactly the same as that given by Tang *et al.* [8] for the LP, HP, BP, and BS filters. To design the digital IIR filters, the augmented objective function with the stability constraints, given by Eq. 14 is minimized.
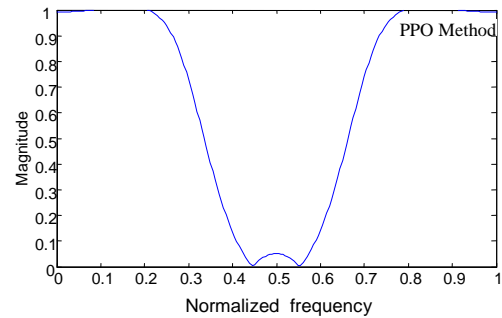

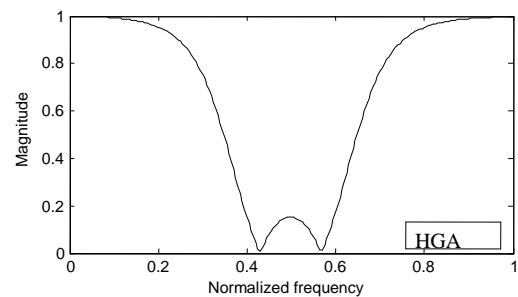Fig 16 Frequency response of BS filter using PPO

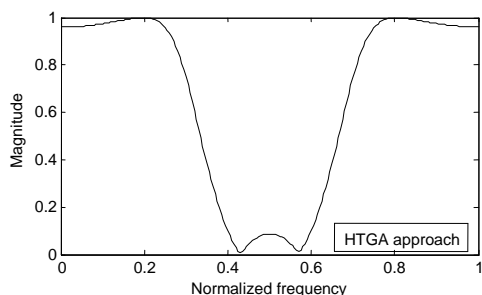Fig 17 Frequency Response of BS filter using HGA[8]

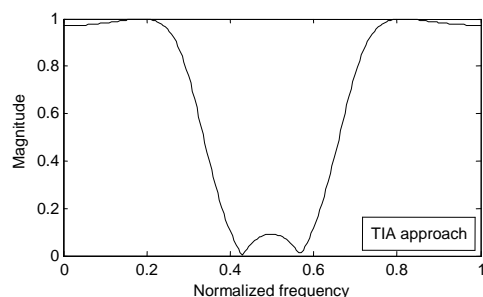Fig 18 Frequency Response of BS filter using HTGA[26]

Fig 19 Frequency Response of BS filter using TIA[27]

That is, for the digital IIR filters designed under the proposed method gives better performances than the GA-based approach given in HGA [8] , HTGA [26] and TIA [27] approaches.
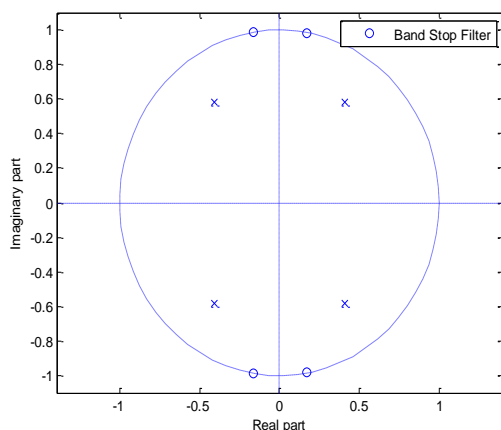

Fig. 20 Pole-zero plot of BS filter

5 Conclusion

This paper proposes predator-prey optimization method for the design of digital IIR filters whereby locally fine tuned by exploratory search method. As shown through simulation results, the PPO method works well with an arbitrary random initialization and it satisfies prescribed amplitude specifications consistently. Therefore, the proposed algorithm is a useful tool for the design of IIR filters. On the basis of above results obtained for the design of digital

IIR filter, it can be concluded that the proposed PPO method hybridized with exploratory search is superior to the GA-based method. Further, the proposed PPO approach for the design of digital IIR filers allows each filter, whether it is LP, HP, BP, or BS filter, to be independently designed. The proposed PPO method hybridized with exploratory search is very much feasible to design the digital IIR filters, particularly with the complicated constraints. Parameters tuning still is the potential area for further research. The unique combination of exploration search and global search optimization method that is predator-prey optimization provided by the two types of algorithms yields a powerful option for the design of IIR filters.

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