Opposition aided Cat Swarm Optimization Algorithm for Optimal Digital IIR High Pass Filter Design

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ABSTRACT: This paper presents a solution methodology for the designing of optimal and stable digital infinite impulse response (IIR) high pass (HP) filter by employing the cat swarm optimization (CSO) technique with oppositional learning. Because of the presence of the denominator terms, the error surface of digital IIR filters is non linear and multimodal. Therefore, the traditional designing techniques usually got trapped in the local minim. CSO is a population based global optimization technique which has global as well as local search capabilities. Here, the multicriterion optimization is used as the design criterion that undertakes the minimization of magnitude approximation error and minimization of ripple magnitudes while satisfying the stability constraints that are imposed during the design process. For the intent of starting with an improved solution set, the opposition based learning strategy is included in CSO. The developed algorithm is used to design the digital IIR high pass (HP) filter and attempts to find the optimal filter coefficients which are approximately close to the desired filter response. The computational results shows that the proposed algorithm is capable of designing the stable and optimal digital IIR HP filter structure that is better to the designs presented by other algorithms.

KEYWORDS: Digital IIR filter, cat swarm optimization algorithm, opposition based learning, high pass filter design, multiparameter optimization.

I.INTRODUCTION

Digital filters nowadays are widely employed in most of the signal processing applications like noise reduction, telecommunication, radars, channel equalization, speech synthesis, biomedical signal processing etc. The digital filters are generally classified as finite impulse response (FIR) filters and infinite impulse response (IIR) filters. The digital FIR filter has a finite duration impulse response and its output depends upon the present and past input values only. Hence, these filters are known as non-recursive. On the other hand, the IIR filter has an infinite or continues impulse response and its output depend upon the present and past input values as well as on the previous output values. Hence, they are termed as recursive filters [1, 2]. Over the past few decades, the digital IIR filters have become the target of growing interest as they provide much better performance, improved selectivity and higher computational efficiency than their FIR counterparts for similar magnitude specifications. Also, they have a much sharper roll-offs in their frequency response than the FIR filters of equal complexity.

The digital IIR filter design process mainly follows two approaches: (i) transformation approach and (ii) optimization approach. The transformation approach involves the transformation of an analog filter to a digital filter for a given set of prescribed specifications [3]. But the performance of digital IIR filters designed by using the transformation approach is not good as they require too much pre-knowledge and in most of the cases return a single solution. Also, the designing of digital IIR filter generally faces two problems that are (i) tendency of the filter to become unstable (ii) filter error surface is multimodal in nature due to which conventional design algorithms may stuck at local minima [4, 5]. The stability problem is handled by imposing stability constraints on the filter coefficients. In order to overcome the

shortcomings of conventional methods and to achieve a global optimal solution, in the past years many nature inspired optimization algorithms have been implemented for the digital IIR filter design problem. Under the optimization approach various methods like the direct search and the gradient search methods have been proposed. Because of multimodal error surface, the conventional gradient-based algorithm easily stuck at local minima [6].

II. LITERATURE REVIEW

In the past few years, to overcome the shortcomings in conventional algorithms numerous nature inspired stochastic optimization techniques have been developed and employed for optimal digital IIR filter designing. Genetic algorithm (GA) has been successfully applied by *Tang et.al.* [7] for the design of digital IIR filter. Then an improved version of GA called hybrid Taguchi genetic algorithm (HTGA) has been proposed by Tsai *et.al.* [8] for the design of optimal digital IIR filters. The HTGA method combines the traditional genetic algorithm having powerful global exploration abilities with the Taguchi method that has the ability to exploit the optimum offspring. Afterwards, Tsai *et.al.* [9] integrated the immune algorithm with the Taguchi method and proposed a hybrid algorithm named Taguchi-immune algorithm (TIA) for optimal digital IIR filter design.

Particle swarm optimization is population based optimization technique developed by Eberhart and Kennedy [10] inspired by natural behavior of bird flocking and fish schooling. It is a computationally fast algorithm and has robust search ability. *Del et. al.* [11] presented a detailed review of PSO. Chaohua *et.al.* [12] used the PSO algorithm for FIR filter design. The conventional PSO algorithm encountered a problem in which it loses global search ability. To overcome this problem Silva *et. al.* [13] proposed the predator-prey optimization (PPO) algorithm and tested it to some benchmark problems. They concluded that PPO method performed effectively better than the PSO on many of these problems. And then, Singh *et. al.* [14] successfully applied and obtained better results as compared to the PPO method.

The seeker-optimization-algorithm based evolutionary method has been successfully implemented for the design of digital IIR filter by Chaohua *et.al.* [15]. The seeker-optimization-algorithm has good local convergence and is capable of providing global minimum solutions but it often require too many objective function evaluations. Afterwards, *Kaur et.al.* proposed methods like real coded genetic algorithm (RCGA) [16] and heuristic search method (HSM) [17]for digital IIR filter design. Poor precision is followed by a binary coded parameter as sometimes it skips the best solution in the coding process.

So, presently the development of new and efficient optimization algorithms that use the magnitude approximation error and ripple magnitudes of both pass band and stop band as performance criteria for the designing of optimal digital IIR filters is very much in progress.

In this paper, the CSO algorithm is used to design the stable and optimal digital IIR HP filter. CSO is proficient in conducting local as well as global search. Further, an improvement in the form of opposition based learning strategy is used with the purpose of starting with better initial solutions by simultaneously checking the opposite solutions. The multicriterion optimization approach is used as the design criterion that undertakes the minimization of magnitude approximation error and minimization of ripple magnitudes of the pass band as well as the stop band while satisfying the stability constraints that are imposed during the design process.

The remainder of this paper is organized as follows. Section III describes the digital IIR filter designing problem. The details of the mechanism for designing the digital IIR filter using cat swarm optimization algorithm and opposition based learning is described in section IV. Section V contains the proposed algorithm steps in detail. In section VI, the performance and statistical analysis of the proposed method has been carried out and the results obtained are compared with the design results in [7], [8], [9], [16] and [17]. Finally, section VII contains the concluding remarks and scope for future work.

III. PROBLEM STATEMENT

The traditional design of digital IIR filter is generally realized by the following difference equation [1]:

$$y(n) = \sum_{i=0}^{M} x_i u(n-i) - \sum_{k=1}^{N} x_{N+k} y(n-k) \tag{1}$$

where, M and N are the number of x_i and x_{N+k} filter coefficients, respectively, such that $N \geq M$. $u(n)$ and $y(n)$ are its input and output, respectively. An equivalent transfer function of digital IIR filter is expressed as follows:

$$H(z) = \frac{\sum_{i=0}^{M} x_i z^{-i}}{1 + \sum_{k=1}^{N} x_{N+k} z^{-k}} \tag{2}$$

where, x_i and x_{N+k} represent the values of the filter coefficients, which produce the desired response. Generally, the digital IIR filter is realized by cascading different first-order and second-order blocks together. The transfer function of the cascaded digital IIR filter is denoted by $H(w, X)$, where X indicates the filter coefficients. The magnitude of $H(w, X)$ is denoted by $|H(w, X)|$. The basic structure of $H(w, X)$ can be stated as [3]:

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

where, N and M denotes the number of filter coefficients of the first and second order sections, $l = 2M + 4(k-1) + 2$ and vector $X = [x_1 x_2 \ldots\ldots x_D]^T$ denotes the filter coefficients of dimension $D \times 1$, such that, $D = 2M + 4N + 1$.

In the IIR filter design process, the coefficients are optimized so that the approximation error function for magnitude is minimized. The magnitude response is specified at K equally spaced discrete frequency points in pass-band and stop-band. The absolute error is denoted by $e(X)$ and is stated below:

$$e(X) = \sum_{k=0}^{K} \left| H_d(w_k) - |H(w_k, X)| \right| \tag{4}$$

where, $H_d(w_k)$ is the desired magnitude response of IIR filter and is given as:

$$H_d(w_k) = \begin{cases} 1 \, for w_k \in passband \\ 0 \, for w_k \in stopband \end{cases} \tag{5}$$

The ripple magnitudes of pass-band and stop-band are denoted by $\delta_p(x)$ and $\delta_s(x)$, respectively and are given as:

$$\delta_1(x) = \max_{w_i}\{H|(w_i)|, x\} - \min_{w_i}\{|H(w_i, x)|\}; \, wi \in passband, \text{and} \tag{6}$$

$$\delta_2(x) = \max_{w_i}\{H|(w_i)|, x\}; \, w_i \in stopband \tag{7}$$

The design of stable digital IIR filter requires the inclusion of stability constraints. Therefore, the stability constraints obtained by using the jury method [18] on the coefficients of the digital IIR filter stated in Eq. (9.1) - Eq. (9.5), are used in the optimization process. The multivariable constrained optimization problem is then stated as:

$$Minimize \, f(x) = e(x) \tag{8}$$

Subject to the stability constraints:

$$1 + x_{2i+1} \geq 0 \, (i=1, 2, \ldots, N) \tag{9.1}$$

$$1 - x_{2i+1} \geq 0 \, (i=1, 2, \ldots, N) \tag{9.2}$$

$$1 - x_{l+3} \geq 0 \, (l=2N+4(k-1)+2, k=1, 2, \ldots, M) \tag{9.3}$$

$$1 + x_{l+2} + x_{l+3} \geq 0 \, (l=2N+4(k-1)+2, k=1, 2, \ldots, M) \tag{9.4}$$

$$1 - x_{l+2} + x_{l+3} \geq 0 \, (l=2N+4(k-1)+2, k=1, 2, \ldots, N) \tag{9.5}$$

Scalar objective constrained multivariable optimization problem is converted into scalar objective unconstrained multivariable optimization problem using exterior penalty function. Augmented objective function is defined as [19]:

$$A(x) = e(x) + r(P_{term}) \tag{10}$$

where,

$$P_{term} = \sum_{i=1}^{N} \langle 1 + x_{2i+1} \rangle^2 + \sum_{i=1}^{N} \langle 1 - x_{2i+1} \rangle^2 + \sum_{k=1}^{M} \langle 1 - x_{l+3} \rangle^2 + \sum_{k=1}^{M} \langle 1 + x_{l+2} + x_{l+3} \rangle^2 + \sum_{k=1}^{M} \langle 1 + x_{l+2} + xl+32 \tag{11}$$

and *r* is a penalty term having a large value.

Bracket function for constraints given in Eqn. (9.1) and Eqn. (9.4) is stated below in Eqn. (12) and Eqn. (13) respectively:

$$\langle 1 + x_{2i+1} \rangle = \begin{cases} 1 + x_{2i+1}, & if(1 + x_{2i+1}) < 0 \\ 0, & if(1 + x_{2i+1}) \geq 0 \end{cases} \tag{12}$$

$$\langle 1 + x_{l+2} + x_{l+3} \rangle = \begin{cases} 1 + x_{l+2} + x_{l+3}, & if(1 + x_{l+2} + x_{l+3}) < 0 \\ 0, & if(1 + x_{l+2} + x_{l+3}) \geq 0 \end{cases} \tag{13}$$

Similarly, bracket functions for other constraints given by Eqn. (9.2), Eqn. (9.3) and Eqn. (9.5) are undertaken. Initial feasible solutions are generated applying constraint handling method [19], in which filter coefficients are randomly perturbed till the satisfaction of constraints. During the run the penalty terms are perturbed to zero by applying random constraint handling.

IV. CAT SWARM OPTIMIZATION

CSO is a heuristic optimization algorithm which imitates the natural behaviour of cats. Cats have a strong interest towards moving objects and own excellent hunting skills. These two behavioural characteristics of the cats are represented by seeking mode and tracing mode, respectively, which are mathematically modelled for solving complex optimization problems [20, 21].

• **Population Initialization**

Initially the number of individuals in the population i.e. the cats that will take part in the optimization process is decided. Every individual in the population has a position made up of *D*-dimensions, velocities for each dimension, a fitness value according to the fitness function and a seeking/tracing flag. The position of the cat represents the candidate solution and the fitness value of each cat represents the accommodation of the cat to the fitness function. The seeking/tracing flag is used to identify whether the cat is in seeking mode or tracing mode. The initial population of cats within the solution search space is initialized as follows:

$$x_{id}{}^t = x_d{}^{min} + R\left(x_d{}^{max} - x_d{}^{min}\right)(d = 1,2,...,D; i = 1,2,...,T) \tag{14}$$

And the velocity for each dimension is mathematically given as:

$$v_{id}{}^t = v_d{}^{min} + R\left(x_d{}^{max} - v_d{}^{min}\right)(d = 1,2,...,D; i = 1,2,...,T) \tag{15}$$

where, $x_{id}{}^t$ and $v_{id}{}^t$ represents the position and velocity of the *i*th cat in *d*th dimension, respectively. And *R* is uniform random number between the range [0, 1]. The population may violate inequality constraints which are corrected by applying the random perturbation method.

• **Fitness Evaluation**

The intend of the optimization process is to minimize the objective function. There is a likelihood of the elements of parent/offspring to violate the constraint. Therefore, a penalty term is introduced and the objective function is penalized and changed to the following generalized form:

$$A_i(X_i) = e_i(X_i) + R(P_{term})(i = 1,2,...,T) \tag{16}$$

where, $X_i = [x_{i1}, x_{i2}, ..., x_{iD}]^T$ and penalty factor is given by Eqn. (11). The value increases with the progress of the algorithm.

● **Oppositional Learning**

The opposition based learning strategy helps CSO algorithm to take a start with some initial random solutions which are improved over time by moving towards the optimal solution. The computational time of an algorithm is an important parameter that is related to the remoteness of the initial guesses from the optimal solution. This can be improved by starting with a better solution while checking the opposite solution in the search space. [22]. Therefore, starting with better guesses adjudged by its objective function has the ability to increase the convergence speed. The same approach is applied during the run, not only to initial solutions but also continuously to each solution in the current population to reach a final optimal solution. This can be mathematically expressed as:,

$$x_{i+T,d} = x_d{}^l + x_d{}^u - x_{id} t \big(d = 1,2,...,D; i = 1,2,...,T\big) \tag{17}$$

where, $x_d{}^l$ and $x_d{}^u$ are lower and upper limits of filter coefficients, respectively and are expressed as follows:

$$x_d{}^l = \begin{cases} x_d{}^{min} & ; t = 1 \\ min\{x_{id}; i = 1,2,\ldots,T\}; t > 1 \end{cases} \tag{18}$$

$$x_d{}^u = \begin{cases} x_d{}^{max} & ; t = 1 \\ max\{x_{id}; i = 1,2,\ldots,T\}; t > 1 \end{cases} \tag{19}$$

● **Seeking mode**

The mixture ratio (*MR*) is used to set the seeking/tracing flag, which decides the number of cats that would randomly be moved into the seeking mode and the tracing mode [23, 24]. The seeking mode corresponds to the global search procedure. This mode emulates the observant behaviour of cats by creating copies of the current solution. Each copy tries to improve the given solution through the exploitation process. After all copies have finished exploiting the current solution, that represent the new position on which the cat has to move, is selected. Seeking mode has four important parameters namely Memory Seeking Pool (*MSP*), Seeking Range of Dimension (*SRD*), Counts of Dimension to Change (*CDC*) and Self position consideration (*SPC*). For a cat, *MSP* is defined as the size of seeking memory for each cat indicating the points sought by each cat. *SRD* dictates the mutative ration for the selected dimensions. If a dimension is selected to mutate, the maximum difference between the new value and the old value cannot be out of the range defined by *SRD*. *CDC* indicates how many dimensions will be varied and *SPS* is a Boolean variable which decides whether the point on which the cat is already standing is a point, for one of the candidates to move to. The seeking mode involves the generation of *t* copies of the present position of *i*th cat, where *t* = *MSP*. If the value of *SPC* is true, let *t* = (*MSP* − 1), then retain the present position as one of the candidates. For each copy, according to *CDC*, randomly plus or minus *SRD* percents the present values and replace the old ones according to the following mathematical equations:

$$X_{id}{}^c = X_{id} + cnvRS_{rd} X_{id} \big(d = 1,2,...,D; i = 1,2,....T\big) \tag{20}$$

$$X_{id}{}^c = X_{id} - cnvRS_{rd} X_{id} \big(d = 1,2,...,D; i = 1,2,....T\big) \tag{21}$$

At the end of the seeking mode, the fitness of all copies is evaluated and from *t* copies the candidate with best fitness is selected and placed at the position of *i*th cat.

● **Tracing mode**

The tracing mode corresponds to the local search technique where the rapid chase of the cat for its pray is mathematically modelled as a large change in its position. Then, the position and the velocity of *i*th cat in the *D*-dimensional space are mathematically expressed as follows:

$$X_i = [x_{i1}, x_{i2},...,x_{iD}]^T \text{ and,} \tag{22}$$

$$V_i = [v_{i1}, v_{i2},...,v_{iD}]^T \tag{23}$$

The global best position of the cat is represented by X_g, where $X_g = [x_{g1}, x_{g2},...,x_{gD}]^T$. In the tracing mode the velocity and the position of the *i*th cat are updated using the following equations:

$$V_{id}{}^n = wV_{id} + CR\left(X_{gd} - X_{id}\right)\left(d = 1,2,...,D; i = 1,2,...,T\right) \qquad (24)$$

$$X_{id} = X_{id} + V_{id}{}^n \left(d = 1,2,...,D; i = 1,2,...,T\right) \qquad (25)$$

where, w represents the inertia weight, C is the acceleration constant and R is a uniform random number distributed in the range [0, 1].

V. DEVELOPED ALGORITHM AND DESIGN RESULTS

The CSO algorithm with the opposition based learning technique is used to design the digital IIR HP filter. The developed algorithm tries to have an optimal IIR HP filter structure while satisfying the stability constraints that are imposed during the design process. The implementation of CSO algorithm for digital IIR HP filter design is explained as follows:

The main procedure of CSO algorithm

1. Initialize the algorithm parameters like number of cats i.e. the population size (*NC*), maximum iteration (*ITMAX*), mixture ratio (*MR*), memory seeking pool (*MSP*), seeking range of dimension (*SRD*), counts of dimension to change (*CDC*), self position consideration (*SPC*), *C1*, x^{max} and x^{min}.
2. Set *t=0*; generate an array of (*D×T*) size of uniform random numbers.
   FOR *d=1 to D*
      FOR *i=1 to T*
         3. Randomly initialize the position of cats in *D*-dimensional space for the population, i.e. $x_{id}{}^0$, using Eqn. (14).
         4. Randomly initialize the velocity for cats, i.e. $v_{id}{}^0$, using Eqn. (15).
         5. Compute the augmented objective function $A_i(x_{id}{}^0)$, using Eqn. (16).
         6. Generate the initial population of individuals using opposition, Eqn. (17).
         7. Compute the augmented objective function $A_{i+T}\left(x_{i+T,d}{}^0\right)$, using Eqn. (16).
         8. Compare $A_i(x_{id}{}^0)$ and $A_{i+T}\left(x_{i+T,d}{}^0\right)$.
      END FOR
   END FOR
9. Arrange A_i in ascending order and select first *T* cats out of *2T* cats in the swarm.
10. Select best member with highest fitness out of *T* cats as $A_b{}^0$ and select the corresponding position as $X_{b_{id}}{}^0$.
WHILE ($T \leq T^{max}$) DO
      11. Increment the iteration count, *t=t+1*.
         IF (seeking/tracing flag=1) THEN
            12. Apply seeking mode steps given in Eqn. (20) and Eqn. (21).
         ELSE
            13. Apply tracing mode steps given in Eqn. (24) and Eqn. (25).
         ENDIF
      14. Select best member A_{best} and corresponding position as $(X_{id})_{best}$.
      15. IF ($A_{best} < A_b{}^0$) THEN
            $A_b{}^0 = A_{best}$;
            $X_{b_{id}}{}^0 = G_{b_{id}}$
         ENDIF
   ENDDO

For designing the digital IIR HP filter, 200 equally spaced points are set within the frequency domain [0, π]. For the purpose of comparison, the lowest order of the digital IIR HP filter is set exactly same as that set by Tang *et al.* [7] and Tsai *et al.* [8] i.e. the order is set equal to 3. The aim is to minimize the magnitude approximation error and ripple magnitudes of both the pass-band and the stop-band, subject to the stability constraints given by Eqn. (9.1) - Eqn. (9.5)

under the prescribed design conditions stated in Table 1. The control parameters used for CSO algorithm are given in Table 2. The final filter model obtained for the HP filter is given in Eqn. (26).

Table 1: Prescribed design conditions for HP filter

Maximum value of $\lvert H(w_i, x) \rvert$	1
Pass band	$0.8 \leq w \leq \pi$
Stop band	$0 \leq w \leq 0.7\pi$

Table 2: Values of control parameters for HP filter

Parameter	Number of cats	Mixture ratio	Maximum number of iterations	Memory seeking pool	Seeking range of dimension	Counts of dimension to change
Notation	*NC*	*XMR*	*ITMAX*	*MSP*	*SRD*	*CDC*
HP	100	0.85	250	5	0.80	0.25

$$H_{HP(z)} = 0.0453 \frac{(z + 1.2999)(z^2 + 0.3389z + 1.2910)}{(z - 0.4553)(z^2 + 1.8050z + 0.8235)} \qquad (26)$$

The results of the developed algorithm for designing the HP filter are summarized in Table 3, where the comparison of the obtained results is carried out with the design results given by other methods like HGA [7], HTGA [8], TIA [9], RCGA [16] and HSM [17]. From the table is can be observed that the developed algorithm is capable of obtaining a lower value of magnitude response error than the other algorithms. In terms of pass band and stop band performance, the proposed algorithm produced results that are superior or atleast comparable to the other well established algorithms.

Table 3: Design results for HP filter

Method	Magnitude Error	Filter order	Pass band performance	Stop band performance
Opposition aided CSO	3.6647	3	$0.9461 \leq \lvert H(e) \rvert \leq 1.0078$ (0.0617)	$\lvert H(e) \rvert \leq 0.1291$ (0.1291)
HSM [17]	4.6635	3	$0.9584 \leq \lvert H(e) \rvert \leq 1.0080$ (0.0504)	$\lvert H(e) \rvert \leq 0.1477$ (0.1477)
RCGA[16]	4.5296	3	$0.9677 \leq \lvert H(e) \rvert \leq 1.0186$ (0.0508)	$\lvert H(e) \rvert \leq 0.1540$ (0.1540)
TIA[9]	4.1819	3	$0.9229 \leq \lvert H(e) \rvert \leq 1.0000$ (0.0771)	$\lvert H(e) \rvert \leq 0.16424$ (0.1424)
HTGA[8]	4.8372	3	$0.9460 \leq \lvert H(e) \rvert \leq 1.0000$ (0.0540)	$\lvert H(e) \rvert \leq 0.1457$ (0.1457)
HGA[7]	14.5078	3	$0.9224 \leq \lvert H(e) \rvert \leq 1.0010$ (0.0779)	$\lvert H(e) \rvert \leq 0.1819$ (0.1819)

The frequency response and pole-zero plots of the designed optimal digital IIR HP filter are represented in Fig. 1 and Fig. 2, respectively. The frequency response plot depicts that the designed HP filter strictly follows the constraints that are imposed during its design process. Also, in the pole-zero plot, all the poles lie inside the unit circle, which proves the stability of the designed HP filter.
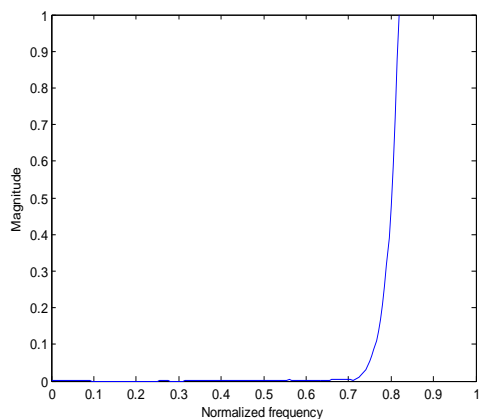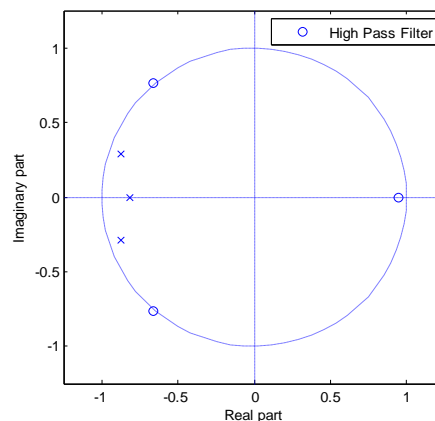
Fig. 1: Magnitude response of the HP filter

Fig. 2: Pole-zero plot of the HP filter

VI. ROBUSTNESS AND STATISTICAL ANALYSIS

Robustness evaluates the performance of an evolutionary algorithm. The CSO algorithm starts with random initialization of the population of cats, which makes randomness an inherent element of CSO. Therefore, the robustness of CSO algorithm to achieve global optimum design solution for order 3 HP filter is determined by having 100 independent trial runs with random seed numbers. The variations in the value of overall objective function have been observed and the maximum value, minimum value, average value and standard deviation in the value is calculated and given in Table 4. From Table 4, it can be observed that the value of standard deviation is very small which indicates that the developed algorithm has outstandingly strong robustness.

To further validate the obtained results and to confirm the effectiveness of the developed algorithm for digital IIR HP filter design, a non-parametric statistical test called the Wilcoxon's signed rank test for single sample is used. This test is conducted on the results obtained by the developed algorithm for the HP filter with a significant level of $\alpha = 0.10$ by comparing them with the results provided by other existing algorithms. Firstly, the sum of positive ranks (R^+) and the sum of negative ranks (R^-) is calculated and then the p-value is determined in each case. The Wilcoxon's signed rank test (Table 5) depicts that the results of the developed algorithm are significantly better then the HGA, HTGA, TIA, RCGA, and HSM algorithms as the p-value is less than 0.10 in all the cases and facilitates the designing of not only stable but optimal digital IIR HP filter.

Table 4: Maximum, minimum, average and standard deviation of magnitude errorfor HP filter

Order	Maximum magnitude Error	Minimum magnitude Error	Average magnitude Error	Standard Deviation of magnitude Error
3	7.1791	4.0762	5.2179	0.4403

Table 5: Statistical analysis results based on Wilcoxon's signed rank test for lower order HP filter

Performance	α	R^+	R^-	p-value
Magnitude approximation error	0.10	0	10	0.033945
Pass-band performance	0.10	1	9	0.072064
Stop-band performance	0.10	0	10	0.033945

VII. CONCLUSION

In this paper, the CSO algorithm together with the opposition based learning strategy is used to design the optimal and stable digital IIR HP filter. CSO possesses qualities like robustness and local as well global search abilities and thus is capable of returning a global optimal solution which is not possible in some conventional optimization algorithms. The proposed approach is executed to solve the multi criterion optimization problem of designing digital IIR HP filter. The experimental results show that the results obtained by CSO algorithm in terms of magnitude response error and ripple magnitudes of pass band and the stop band are better than the results given in [7], [8], [9], [16] and [17] and is very much feasible for the designing of digital IIR HP filter when the multi criteria, complicated constraints, and design requirements are involved. Further, the pole-zero plot of the digital IIR HP filter depicts the stability of the designed filter as all the poles lies inside the unit circle. For future research, parameter tuning is still a potential area. Also, the proposed method can be used to design higher order multi dimensional filters, adaptive filters and filter banks.

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