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Optimal High Pass FIR Filter Based on Adaptive Systematic Cuckoo Search Algorithm

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Abstract**:** *This paper presents the design of a desired linear phase digital Finite Impulse Response* (*FIR*) *High Pass* (*HP*) *filter based on Adaptive Systematic Cuckoo Search Algorithm* (*ACSA*)*. The deviation, or error from the desired response, is assessed along with the stop-band and pass-band attenuation of the filter. The Cuckoo Search algorithm* (*CS*) *is used to avoid local minima because the error surface is typically non-differentiable, nonlinear, and multimodal. The ACSA is applied to the minimax criterion* (L_∞*-norm*) *based error fitness function, which offers a better equiripple response for passband and stopband, high stopband attenuation, and rapid convergence for the developed optimal HP FIR filter algorithm. The simulation findings demonstrate that when compared to the Parks McClellan* (*PM*)*, Particle Swarm Optimization* (*PSO*)*, CRazy Particle Swarm Optimization* (*CRPSO*)*, and Cuckoo Search algorithms, the proposed HP FIR filter employing ACSA leads to better solutions.*

Keywords**:** *Cuckoo search algorithm, High pass filter, Minimax, Swarm Intelligence, Weighted error.*

1. Introduction

A digital filter system boosts or concentrates specific signal qualities by applying mathematical operations to a discrete-time sampled signal. Filtering is the process of passing desired frequencies and stopping the undesired ones through the system [1]. Two types of digital filters are discussed here, i.e., FIR and Infinite Impulse Response (IIR) filters. FIR filters are attractive because they possess linear phase and are stable, give precise performance characteristics, could be designed both in software and hardware platforms IIR filters require less memory with fewer coefficients [2]. The optimal filter design offers a roughly flat pass-band and attenuates the stop-band to infinity.

Because of their numerous applications in areas like control systems engineering, biomedical signal processing, audio systems, image processing, etc., digital filters have attracted attention during the past few decades. Digital filters are used in control systems engineering for system modelling, identification, stabilization [3] and wavelets denoising [4]. In biomedical signal processing, digital filters are primarily used for medical images like ECG, EEG, and MRI images denoising [5, 6]. Digital filters are employed in audio systems for a variety of purposes, including equalization, crosstalk cancellation, channel up mixing, and acoustic room compensation [7].

In literature, the desired frequency response is obtained by generating a set of filter coefficients using several design approaches with a challenge to minimize pass band and stop band ripples simultaneously along with sharp cutoff and reduced filter order. Digital FIR filters cannot be designed optimally using traditional design concepts. The advantages of optimization techniques like evolutionary computation, particle swarm, cuckoo search algorithm, artificial bee colony algorithm, etc. have been highlighted in several studies over the past two decades that highlight the drawbacks of conventional techniques. It has been demonstrated that the Adaptive Genetic Algorithm (AGA), which has been used to design the best FIR low pass filters, performs better than other PSO iterations [8]. Optimized filter coefficients are used to propose adaptive discrete wavelet transform [9]. To create and improve FIR digital filters, an upgraded PSO algorithm called refrPSO that is based on the refracting opposite learning model is employed [10]. For frequency sampling-based FIR filter design, the Artificial Bee Colony (ABC) algorithm is used [11]. Cuckoo Search Algorithm (CSA) exhibits better performance in comparison to the GA [12], PSO [13, 14] and craziness based PSO [15].

Several hybrid algorithms such as GA and SA or more adaptive methods have been suggested for filter design. In [16], a hybrid PSO and fitness-based Adaptive Differential Evolution PSO method (ADEPSO) is used to effectively design linear phase FIR filters. [17] provides an overview of PSO and other technique hybridization ideas. FIR low pass digital filter design uses a hybrid artificial bee colony algorithm [18]. A coherent integration of the Moth Flame Optimization (MFO) and Powell's Pattern Search (PPS) techniques is presented for the optimal design of a Finite Impulse Response (FIR) filter in order to keep a fine balance between the search technique's exploitation and exploration capabilities [19].

This work performs a thorough ACSA study for the FIR HP filter, which can be broadened to design various FIR filters (low pass, band pass and band stop). In order to obtain low magnitude ripples in the passband and significant attenuation in the stopband, the filter coefficients using ACSA are calculated. The achieved results are compared with those of PSO, CRPSO, and CSA optimization methods.

The rest of the paper is structured as follows: The filter design issue is described in Section 2. In Section 3, the applied optimization algorithms are covered. The simulation analysis and findings are discussed in Section 4. The paper is concluded in Section 5.

2. Problem formulation

To design FIR high-pass filter, the response of filter $H(e^{j\omega})$ is compared with the frequency response desired for high pass filter with filter coefficients $h[n]$, where n ranges between 0 to N, and N is the order of the filter. Let $I_{\mathrm{HP}}(\omega)$ be the desired frequency response, and can be defined as

(1) $$I_{\mathrm{HP}}(\omega) = \begin{cases} 0, & \omega \in [0, \omega_{\mathrm{c}}) \text{ stopband}, \\ 1, & \omega \in [\omega_{\mathrm{c}}, \pi] \text{ passband}, \end{cases}$$

ω_{c} is cut off frequency. $H(e^{j\omega})$ is calculated from $h[n]$ of filter as

(2) $$H(e^{j\omega}) = \sum_{n=0}^{N} h[n] e^{-j\omega n},$$

$h[n] = h[N-n], 0 \leq n \leq N,$ implies the condition for symmetric coefficients which leads to:

(3) $$P(\omega) = h\left[\frac{N}{2}\right] + 2\sum_{n=1}^{\frac{N}{2}} h\left[\frac{N}{2} - n\right] \cos(\omega * n),$$

(4) $$P(\omega) = h[L] + 2\sum_{n=1}^{L} h[L-n] \cos(\omega * n),$$

(5) $$P(\omega) = \sum_{n=0}^{\frac{N}{2}} p[n] \cos(\omega * n),$$

where $P(\omega)$ is amplitude response and $p[0] = h[L]$, $p[n] = 2h[L-n]$, $1 \leq n \leq L$.

The error, i.e., objective function is obtained and minimized by approximating $P(\omega)$ to response of an ideal filter, i.e., $I_{\mathrm{HP}}(\omega)$. Various types of error functions based on L_1-norm, L_2-norm and Chebyshev L_∞-norm; also known as minimax solution are used for the design purpose. L_1-norm results in a high stopband attenuation (Astop) and flat passband. In L_2-norm based filters, high overshoot is obtained near the discontinuity. Here, the L_∞-norm is used to calculate the error function $E(\omega)$ given in the next equation as minimax solution leads to equal ripples in both passband and stopband with the smallest maximal error and the smallest overshoot amongst L_1, L_2 & L_∞ norms [20]:

(6) $$E(\omega) = \max_{\omega} |P(\omega) - I_{\mathrm{HP}}(\omega)|.$$

In this paper, error is calculated using the PSO, CRPSO, CSA and ACSA optimization techniques and the better filter is the one, which has lower error function values.

3. Employed algorithms

Here, we will first discuss the Adaptive Cuckoo Search Algorithm and the concept of dynamic decreasing switching parameter used in Gbest-Cuckoo Search Algorithm (GCSA). Then, these two approaches are combined to form the dynamic decreasing switching parameter based Adaptive systematic Cuckoo Search Algorithm (ACSA) and ACSA will be used to optimize FIR HP filter.

3.1. The Adaptive Cuckoo Search Algorithm

CSA is a metaheuristic optimization technique that was developed in 2009 and is based on the cuckoo bird's breeding strategy with three key criteria. "The host cuckoo can either discard the egg or leave the nest and make a new one somewhere else"

[21]. The next equations define the local and global random walks in CSA, respectively. They have established parameters in [22]:

(7) $$x_i(t+1) = x_i(t) + \alpha s \otimes H(P_a - \varepsilon) \otimes \left(x_j(t) - x_k(t)\right),$$

(8) $$x_i(t+1) = x_i(t) + \alpha L(s,\lambda).$$

Here, depending on the search space's dimension, α is a constant and $L(s,\lambda)$ is represented as a random walk through Levy flight [23]. As demonstrated in the next equation, the value of the switching parameter is changed linearly with the number of iterations in order to boost CSA efficiency:

(9) $$P_{aC_i} = (P_{a\mathrm{Max}} \times C_i)/\mathrm{Epoch}.$$

Their parameters are defined in Table 1.

Table 1. Dynamic Switching parameter definition [22]

Parameters	Description
C_i	Current iteration
Epoch	Total number of iterations
P_{aC_i}	Current iteration switching parameter
$P_{a\mathrm{Max}}$	Maximum switching parameter value

3.2. Gbest-Cuckoo Search Algorithm

CS significantly improves global optimization. To improve the search strategy's balance between exploitation behaviour and exploration while also automating it, the Gbest-guided Cuckoo Search algorithm (GCS) is used [20]. GCS gives information ranging from the global best nests on earth to abandoned. Rather than maintaining a constant value of λ =1.5, here we updated λ as mentioned in the next equation:

(10) $$\lambda = (\lambda_{\max} - \lambda_{\min}) * \frac{(\mathrm{Epoch-iter})}{\mathrm{Epoch}} + \lambda_{\min},$$

where $\lambda_{\max}$ and $\lambda_{\min}$ represents the minimum and maximum value of λ, respectively. The parameter P_a can be appropriately adjusted to increase the convergence rate. Therefore, P_a is changed based the next equation to make the algorithm self-tunned:

(11) $$P_a = \frac{\mathrm{rand}}{D},$$

where D is the dimension of the problem, and "rand" is the random number, rand$\in [0,1]$.

3.3. Adaptive Systematic Cuckoo Search Algorithm

The most significant drawback of CSA is that parameter tuning is necessary, which makes it less effective than GCS. In GCS, no tuning of parameters are used in the form of λ and P_a as already discussed in Equations (10) & (11), respectively. In order to make GCS more efficient, Adaptive systematic Cuckoo Search Algorithm (ACSA) is proposed in which we varied mean free path (λ) as mentioned in Equation (10). Additionally, it is proposed that as the iterations increase, value of the switching parameter, P_a, linearly decreases as shown in the next equation. This will improve the exploitation capability of the ACSA:

(12) $$P_{aC_i} = P_{a\mathrm{Max}} - \left(\frac{P_{a\mathrm{Min}} \times C_i}{\mathrm{Epoch}}\right),$$

Their specifications are listed in Table 2.

Table 2. Dynamic Switching parameter definition

Parameters	Description
P_{aC_i}	Switching parameter of the current iteration
$P_{a\text{Max}}$	Maximum switching parameter value
$P_{a\text{Min}}$	Minimum switching parameter value
C_i	Current iteration
Epoch	Total number of iterations

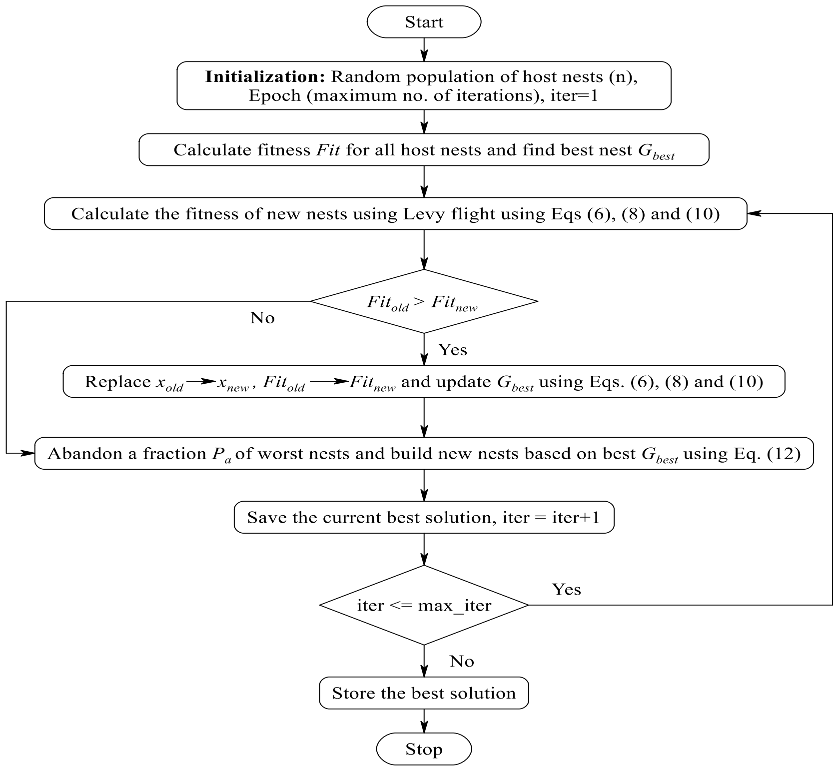

Fig. 1. ACSA flowchart

The flowchart of proposed ACSA algorithm is illustrated in Fig. 1, and the following are specific two steps for utilizing ACSA to design a FIR filter.

Step 1. Initialization

A. Initialize the order of the HP FIR filter *N*=20, the maximum number of iterations Epoch, the number of host nests *n*, lower and upper bounds of digital filter coefficients, –1 and +1. In this article, we initialize *n* = 25 and Epoch = 1000 for the design of HP FIR filter.

B. The set of *N*+1 filter coefficients (candidate solutions) shown as $a = [a_0, a_1, \dots, a_N]^{\mathrm{T}}$ are represented by randomly generated *n* host nests.

C. Consider the fitness function (Fit) for the design of the digital high pass FIR filter also known as error objective function shown in Equation (6).

Step 2. Iteration

A. Compute the Fitness function $\mathrm{Fit}_{\mathrm{old}}$ for the randomly generated nest *i* by using levy flight in Equations (6), (8) and (10).

B. Compute the fitness function Fit_{new} for the randomly generated nest k by using levy flight in Equations (6), (8) and (10).

D. Compare the fitness values. If $\text{Fit}_{\text{old}} > \text{Fit}_{\text{new}}$ then egg i will be used in place of egg k.

E. Remove the worst nest according to the probability P_{aC_i} and build new nests based on best G_{best} using Equation (12).

G. Save current best solutions and update the value of "iter", i.e., iter = iter + 1.

H. Find best nest that utilizes optimum high pass filter coefficients a_b by repeating steps A-G until the stopping criterion (iter ≤ max iter) is achieved.

By adjusting the various control parameters, the optimization algorithm's performance for a particular problem can be significantly improved. Controlling parameters for each algorithm are selected in this work after multiple simulations are given in Table 3.

Table 3. FIR high pass filter design control parameters

Parameters	Symbol	PSO	CRPSO	CSA	ACSA
Population size	Popsize	90	90	25	25
Inertia weight	W	0.9-0.4	0.9-0.4	-	-
Maximum iteration cycle	Epoch	1000	1000	1000	1000
Particle velocity	$v_{\min}$; $v_{\max}$	0.01; 1	0.01; 1	-	-
Learning parameters	C_1; C_2	2; 2	2; 2	-	-
Discovering rate of alien eggs	P_a	-	-	0.25	-
Number of nests	n	-	-	25	25
Maximum switching parameter value	$P_{a\text{Max}}$	-	-	-	0.5
Minimum switching parameter value	$P_{a\text{Min}}$	-	-	-	0.25
Filter coefficients limits		–1, +1	–1, +1	–1, +1	–1, +1

4. Simulation results and analysis

In order to design digital FIR high pass filter, the error function in Equation (6) has characteristics that are extremely nonlinear, non-convex, and multimodal. To discover the best answer, i.e., filter coefficients, has led to the adoption of computationally effective evolutionary & swarm intelligent algorithms. Around 50 simulations with arbitrary changes in the parameters are carried on Windows 10 Home with Intel® Core™ i5-4200U CPU 2.30 GHz, 6 GB RAM running the MATLAB R2015a and best results are presented. The filter order, N=20, and cut-off frequency, $\omega_c = 0.45\pi$, are design parameters. PSO, CRPSO, CSA, and ACSA approaches are used to reduce the digital filter error function. Table 4 reports the 20th order digital FIR symmetric high pass filter optimal coefficients which are obtained using PM, PSO, CRPSO, CSA, and ACSA algorithms.

Using several applicable optimization strategies, the magnitude response (in dB) of the 20th order digital FIR HP filter is graphically compared in Fig. 2. The stopband is enlarged and displayed in Fig. 3 to more clearly illustrate the performance of all the applied methods. Fig. 4 displays the 20th order FIR high pass filter's larger passband response. The plots clearly illustrate that ACSA has the highest minimum Attenuation in the Stopband (Astop).

Table 4. The 20th order FIR high pass filter optimized coefficients

No	Optimization algorithm	Optimized coefficients (h_k), $0 \le k \le N$, N=20 $h_k = h_{N-1-k}$
1	PM	–0.1863758845828, 0.04644467460062, 0.08515327450669, 0.05432463761543, –0.01518974100395, –0.01289178007653, 0.07985895679551, 0.11947030919084, –0.02932159098185, –0.28974723718015, 0.57905517463708
2	PSO	0.01186758764384, –0.00886712467503, –0.00006530694347, 0.04992096255993, –0.00025319972781, –0.04962977797468, 0.00005252454461, 0.10461458217427, 0.00277709062765, –0.31551696734379, 0.49956064758609
3	CRPSO	0.0117735147941, –0.00886564763796, –0.00136354303979, 0.04049119945231, –0.00074037826118, –0.04497943617491, 0.00025177187698, 0.10632370323137, 0.00021403189245, –0.31474552822784, 0.49952972552265
4	CSA	0.01263150443432, –0.01024987224338, –0.00358988118388, 0.04302469905999, –0.00237777218853, –0.0496723876118, 0.00075668476165, 0.10430541043714, 0.00194701644974, –0.31602852556023, 0.49959962213189
5	ACSA (proposed)	0.01266279421033, –0.03321594702298, 0.00629818991882, 0.03909925402334, –0.00291851200238, –0.04987233875317, –0.00001355966039, 0.10425767752073, –0.00262729189841, –0.3166314272823, 0.49998146109844

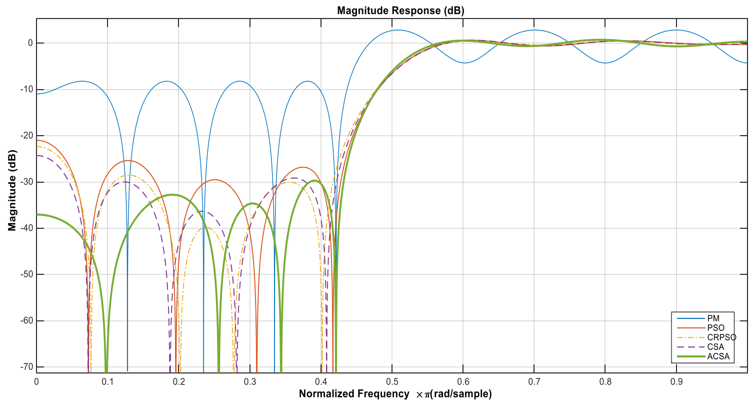

Fig. 2. The 20th order FIR high pass filter magnitude response (dB)

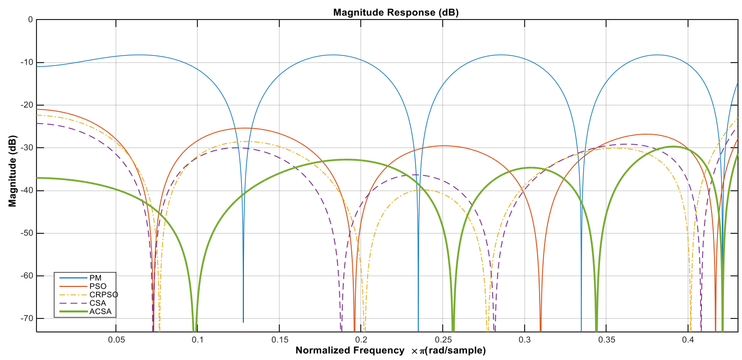

Fig. 3. The 20th order FIR high pass filter enlarged stopband response (dB)

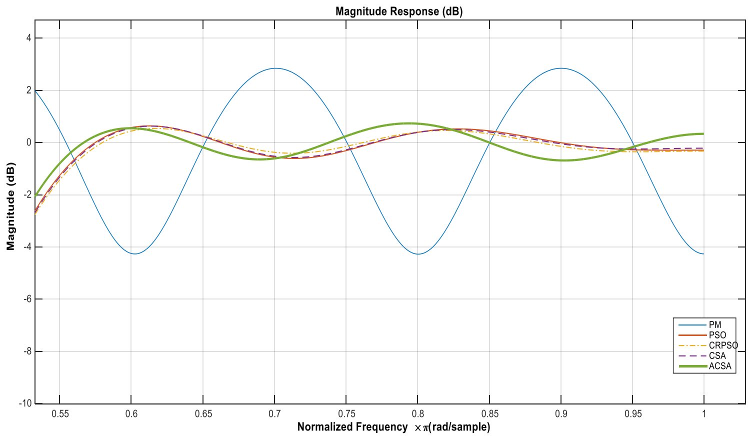

Fig. 4. The 20th order FIR high pass filter enlarged passband response (dB)

Table 5 presents and compares the performance metrics for the design of the digital FIR HPF using PM, PSO, CRPSO, CSA, and ACSA. As compared to CSA (–24.28 dB, 0.0611), CRPSO (–22.36 dB, 0.0763), PSO (–20.98 dB, 0.0894), and PM (–8.21 dB, 0.3884), ACSA has the lowest stopband attenuation and ripples of –29.70 dB, 0.0328. It is also shown in Table 3 that the algorithm execution time (s) for ACSA is minimum, i.e., 6.05 s as compared to CSA (8.81 s), CRPSO (10.34 s), PSO (11.66 s) and PM (15.05 s), respectively. This is due to the fact that all parameters in ACSA are self-tuned and leads to fast convergence.

Table 5. The 20th order FIR high pass filter performance evaluation

Algorithm	Minimum Stopband Attenuation (dB)	Stopband Ripples	Maximum Passband Attenuation (dB)	Passband Ripples	Execution Time (s)
PM	–8.21	0.3884	2.85	0.1625	15.05
PSO	–20.98	0.0894	0.74	0.0424	11.66
CRPSO	–22.36	0.0763	0.66	0.0377	10.34
CSA	–24.28	0.0611	0.61	0.0353	8.81
ACSA	–29.70	0.0328	0.53	0.0306	6.05

Fig. 5 displays the designed digital FIR HPF's normalized magnitude response. ACSA gives the minimum discontinuity overshoot in the ideal filter, whereas PM produces the most. When compared to the PM, PSO, CRPSO, and CSA algorithms, it has been found that ACSA produces the minimum passband ripples.

Fig. 6 displays an enlarged normalized stopband response. ACSA offers the highest minimum stopband attenuation.

The mean, variance, and standard deviation of the stopband and passband ripples are illustrated in Table 6.

The convergence curve of 20th order FIR high pass filter using PSO, CRPSO, CSA and proposed ACSA is shown in Fig. 7. It can be seen that FIR high pass filter design using ACSA algorithm achieves convergence faster as compared to PSO, CRPSO and CSA algorithms due to self-tuned parameters.

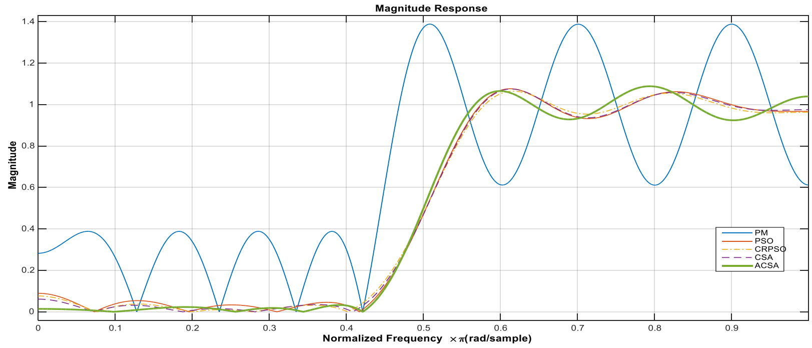

Fig. 5. The 20th order FIR high pass filter normalized magnitude response

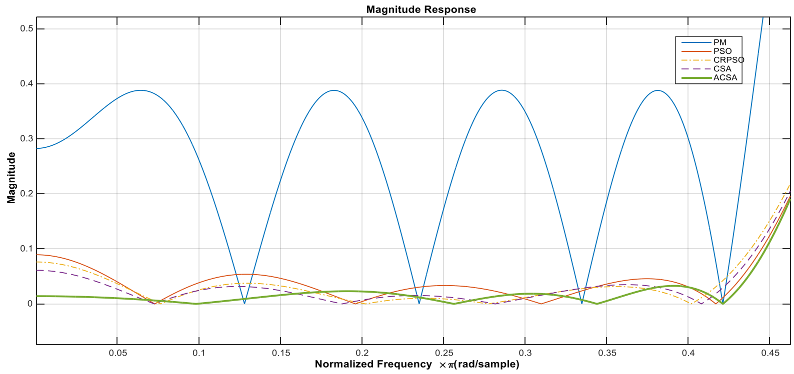

Fig. 6. The 20th order FIR high pass filter enlarged normalized stopband response

Table 6. The 20th order FIR high pass filter qualitative analysis

Algorithm	Stopband attenuation (dB)			Passband ripple		
	Mean	Variance	Standard deviation	Mean	Variance	Standard deviation
PM	–22.1054	–52.2457	–26.1229	0.1721	0.0235	0.1533
PSO	–26.6552	–58.1542	–29.0771	0.0914	0.0156	0.1249
CRPSO	–29.4521	–60.1425	–30.0713	0.0625	0.0124	0.1114
CSA	–32.2576	–63.4524	–31.7262	0.0459	0.0076	0.0872
ACSA	–35.4582	–62.4256	–31.2128	0.0386	0.0045	0.0671

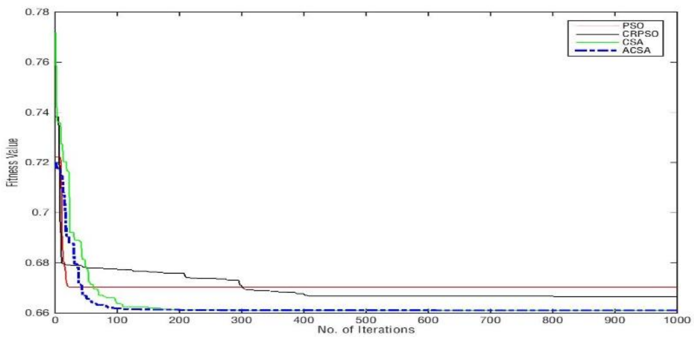

Fig. 7. Convergence curve of 20th order FIR HPF using PSO, CRPSO, CSA and ACSA

5. Conclusion

In this article, a 20th order FIR HP filter is designed using a variety of optimization approaches, including PSO, CRPSO, CSA, and proposed ACSA. The suggested design strategy for designing the best band pass and low pass filters can be implemented using the transformation techniques. In comparison to other optimization techniques with similar parameters, ACSA provided the best result. The FIR HP filter with an ACSA basis exhibits the lowest passband and stopband ripples and the maximum stopband attenuation. Additionally, it is executed with the fewest errors and is the fastest. The convergence profile illustrates how the suggested ACSA also outperforms PSO, CRPSO, and CSA approaches in terms of exploration and improved exploitation.

***Conflict of interest*:** The authors declare that they have no conflict of interest.

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