Seeker Optimization for Linear Phase Fir Filter Design

Harmandeep Kaur, Satish Saini, and Amit Sehgal

Abstract In this paper, filter design procedure is analyzed using seeker optimization technique to design an optimal finite impulse response (FIR) filter with desired parameter specifications. Using these algorithms, the optimum impulse response coefficients of the different finite impulse response filter are determined to fulfill their exact output. A fitness function based on the error is generated in which we can specify the desired levels of δ_p and δ_s individually. Simulative results of these techniques are presented and compared in conformity with their select band and reject band ripples. The techniques developed are mainly useful for digital signal processing applications as clearly indicated by the results that it forms a good platform for newer applications.

Keywords Seeker · Bat · FIR filter

1 Introduction

With the various advancements in the transformation of digital signal, filters based on the digital techniques are gaining much more importance instead of analog filters. Digital filtrate is a system that uses digital signal as input and provides digital signal as output after filtering. These are categorized into two: FIR and IIR filters reliant to size of its impulse. Each filter possesses its own advantages and disadvantages. Designing parameters for FIR filter, which are to be considered during the designing of filters, are mentioned as: select band frequency, reject band frequency, ripples, fading, filter coefficients, filter order, etc. [1–4]. FIR filter has numerous advantages over IIR filter which leads to its popularity among the researchers. The implementation of FIR filter is much simpler as it requires no feedback. By making the coefficients of the filter to be

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symmetrical, linear phase response can be achieved; thus, it allows consistent group delay [5]. Filter designing involves determining the filter coefficients and filter order which satisfy the required filter stipulations, for example, the frequencies of select band and reject band, select band and reject band width, and select band and reject band ripples as well as attenuation. The FIR filters feasibly be projected using various techniques as an illustration window design technique [6–9], frequency sampling [6, 10] weighted least squares design [6], and Parks–McClellan method (equiripple or optimal method) [2, 11]. Traditionally, windows method is the most common of all these. But, in case of windows method, a fabricator will have to be negotiable between one or two parameters.

So, optimization techniques gained a lot of interest of the candidate researchers to design the filter with appropriate design conditions such as evolutionary optimization techniques. Previously, the swarm-based optimization techniques and genetic algorithms (GA) were used to implement FIR filter design such as particle-based optimization (PSO). Various techniques in particular Parks–McClellan method, genetic algorithm (GA) [12, 13], particle swarm optimization (PSO) [12, 14, 15], differential evolution (DE) optimization [16–18], teaching–learning-based optimization (TLBO) [19–21] seemed to be exerted for the projection procedure of FIR filters. Yang proposed an innovative evolutionary optimization technique identified to be Bat algorithm [22]. Severino et al. designed a FIR filter by the usage of PSO and Bat techniques [23]. It is being used in almost every field such as optimization [22, 24], filter designing [23], image processing [25, 26], data mining, feature selection, fuzzy logic [27, 28], artificial neural networks [29, 30], and many more. SOA [31] mimes the doings of individual hunt populace to resolve actual optimization issues. It works on the basis of human searching to reach at the desired optimum solution. A group of humans known as population are taken. Each individual in this are known as seekers. Each seeker has its own center position, search radius, trust degree, and search direction according to which it updates its position. Seeker optimization finds its use in almost every field of study especially in engineering and technology and are successfully implemented in various problems such as in [32] SOA method has also been used for optimal reactive power dispatch problem. In [33], it has been used for designing IIR filter, and as per the literature review, it is not been used much for optimizing FIR filter parameters.

In the current paper, comparison is done between the seeker, Bat and PSO optimization algorithms to design the FIR filter. The simulation results based on this design are presented here. The article is organized as per the aforementioned manner. Module 1 presents the introduction. Module 2 describes the FIR filter model. In module 3, filter design using optimization technique is discussed. In module 4, outcome of the simulative environment is presented. Finally, module 5 concludes the paper.

2   Optimization Algorithms for FIR Filter

The major aim in the present study is to project an optimal digital FIR filter with better design considerations with the use of seeker optimization technique. The symmetrical nature of the coefficients requires only half of the coefficients to be optimized which are then combined to form $N + 1$ count of coefficients. Various parameters that are considered during the optimum filter designing are pass band and stop band frequencies (w_p and w_s), flat pass band, highest reject band attenuation, pass band and stop band ripples (δ_p and δ_s), and short transition width.

Error function/fitness function/objective function is the major parameter to be considered in all optimization algorithms. While designing the filter, coefficients are changing the values in a manner with the purpose of the minimization of error function. The Parks–McClellan algorithm uses the weighted approximate error for FIR filter design as presented in (1).

$$E(w) = M(w)[K(w_k) - K_i(w_k)] \tag{1}$$

$K(w_k)$ illustrates the frequency output of desired filter, and ($K_i(w_k)$) symbolizes the frequency output of actual filter. M (w) represents the weighting function. Fixed proportion of δ_p/δ_s is the key disadvantage of PM technique. An umpteen number of error equations have been and are being used in variant researches as given in [34–36]. The Lp standard approximation error is indicated as:

$$\text{Error} = \left\{ \sum_{i=0}^{k} [||K_d(w_k)| - |K_i(w_k)|||]^p \right\}^{\frac{1}{p}} \tag{2}$$

Minimum value of the error equation will be interpreted as the optimum one. A new set of coefficients will be generated using the optimal value of fitness function. By individually specifying the required values for δ_p and δ_s, flexibility in the error equation may further be improved by specifying the error equation as presented in [3]

$$J_1 = \max_{w \leq w_p} \left(|E(w)| - \delta_p \right) + \max_{w \geq w_s} \left(|E(w)| - \delta_s \right) \tag{3}$$

2.1   PSO Algorithm

PSO algorithm is a swarm-dependent technique based upon the swarm of birds or school of fish that follow the path by learning from their fellow mates. Kennedy and Eberhart [14] established it in 1995. It has the advantage of not getting trapped in the local optimal solution but solves the problem at a global approach [15]. Every

individual varies their parameters in accordance with the group of individuals (known as swarm), especially position which has two values—personal or local best (pbest) and group (global) best (gbest). Each particle modifies the location and velocity of its own in consonance with the following equations.

$$\text{Ve}_j^{(g+1)} = w * \text{Ve}_j^g + C_1 * r_1 * \left(\text{pbest}_j^g - S_j^g\right) + C_2 * r_2 * \left(\text{gbest}^g - S_j^g\right) \quad (4)$$

Ve_j^g symbolizes the jth particle vectors velocity at gth iteration; w states weighting factor; C_1 and C_2 are the cognitive functions known as positive weighting functions; r_1 and r_2 represent the random values in within 0 and 1; S_j^g is the occurant position of jth particle vector $h(n)$ at gth iteration; pbest_j^g represents the local best of the jth particle at the gth iteration; gbest^g represents the global best of the entire group at the gth iteration.

The position is updated in correspondence to the undermentioned equations:

$$X_j^{(g+1)} = X_j^g + V_j^{(g+1)} \quad (5)$$

2.2 Bat Optimization Algorithm

Bat optimization is a search algorithm depending upon the behavior of bats and their echolocation capability. It is proposed by Yang [22] and works according to the search behavior of bats for their food. It senses the distance using echolocation property and takes advantage of frequency equation. To utilize this algorithm for any optimization problem, initialized values for velocity, position, minimum frequency, wavelength, and loudness (speech intensity) values are set to find out the target.

Bat Motion and Variations of Loudness and Pulse Rates

Each bat has its initialized velocity v_i, position p_i, and pulse frequency q_i in a solution space.

$$q_i = q_{\min} + (q_{\max} - q_{\min})\beta \quad (6)$$

where $q_{\max}$ and $q_{\min}$ are maximal and minimal emission frequencies which are assigned a value uniformly. Initially, value of a frequency is haphazardly assigned for each bat and is drawn consistently from $[q_{\max}, q_{\min}]$. The values for the vector $\beta \in [0, 1]$ are considered to be the random value taken from a uniform distribution.

The new velocity position v_i^t and position z_i^t of the bats are updated at every time step t in accordance with the velocity and position equations as follows:

$$v_i^t = v_i^{t-1} + \left(z_i^{t-1} -- z*\right)f \quad (7)$$

where $z*$ states the present best position (result) globally that is taken after the comparison of the entire solutions of n count of bats.

$$z_i^t = z_i^{t-1} + z_i^t \qquad (8)$$

A fresh solution is bring forth locally for each bat utilizing arbitrary walk after the selection of a solution among the present best solutions.

$$z_{\text{new}} = z_{\text{old}} + \varepsilon L^t \qquad (9)$$

where ε symbolizes random count selected within -1 and 1, i.e., $\varepsilon \in [-1, 1]$

$$L_i^{t+1} = \alpha L_i^t \qquad (10)$$

$$p_i^{t+1} = p_i^0 \big[1 - \exp(-\gamma t)\big] \qquad (11)$$

assuming L_i and p_i as the loudness value and pulse rate and are needs to be updated in accordance with the proximity of the prey with an increase in the number of iterations. On reaching near the prey, the decrease in loudness value is seen, but on the contrary, the speed of emitted pulse rises. The values of loudness are specified as per the convenience of the problem to be solved; usually, $L_o = 1$ and $L_{\text{min}} = 0$ are chosen for any problem where $L_{\text{min}} = 0$ indicates that the search of a bat for its prey is successful and is currently not sending any pulses for further processing. α and γ are constant values, and generally, for almost all simulative analysis, these are taken to be equal, i.e., $\alpha = \gamma$.

2.3 Seeker Optimization Algorithm

Seeker optimization (SOA) mimes the doings of individual hunt populace to resolve actual optimization problems. It works on the basis of human searching to reach at the desired optimum solution. A group of humans known as population are taken. Each individual in this are known as seekers. Each seeker has its own center position, search radius, trust degree, and search direction, and in accordance with these parameters, each seeker updates its position [31–33]. The final decision-making is done while considering these four parameters. Each seeker is initialized with a random value, and afterward, their positions are changed as per the following equation:

$$Z_{\text{id}}(t + 1) = Z_{\text{id}}(t) + \alpha_{\text{id}}(t)\beta_{\text{id}}(t) \qquad (12)$$

where $\alpha_{\text{id}}(t)$ and $\beta_{\text{id}}(t)$ are the step length and search direction of the ith seeker and dth dimension or variable. $\beta_{\text{id}} = 1$ indicates that the ith seeker moves in the positive direction on the dimension, whereas $\beta_{\text{id}} = -1$ indicates its movement in negative

direction and $\beta_{id} = 0$ shows that no movement of the ith seeker. Step length and search direction are updated at each iteration depending upon the following factors.

2.3.1 Filter Design Using Seeker Algorithm

For designing FIR filters, undermentioned steps are implemented:

Step 1: Determine the controlling parameters for FIR filter such as select band and reject band frequencies, order of filter, and select band and reject band ripples.

Step 2: Specify the parameters for seeker optimization such as maximum population number (n_p) of seeker strings, where each string has ($N/2 + 1$) count of filter coefficients, maximal count of loops, and initialization for the values for s number of seekers. Also, initialize the values of highest and lowest frequency and minimum and maximum value of membership degree value (μ_{min} and μ_{max}).

Step 3: Initialize the arrays for the position values.

Step 4: Calculate the fittingness value for any and all individuals.

Step 5: Upgrade the best suited location of all individuals and select adjacent individual of all seekers.

Step 6: Compute the hunt trajectory as well as step size for all seekers, after that amend the location of each seekers.

Step 7: Upgrade the location for all seekers and measure the fitness from these updated values. Update the new solutions otherwise repeat the process from step 4.

Step 8: Generate the filter coefficients using these updated solutions by selecting the best seeker among the entire group.

3 Results

In the current module, the outcome of the codes simulated on MATLAB environment for designing an optimal FIR filter of the all four kinds of filters is presented. Filter order is kept to be 40 after comparing the different orders for the same problem. The sampling frequency is equal to $f_s = 1$ Hz, and count of frequency samples is 512. The required guidelines of the filter to be projected using optimization techniques are taken as: $\delta p = 0.1$, $\delta s = 0.01$. The codes of all the optimization techniques are run for 100 iterations to procure the optimal output, i.e., number of iterations considered for the optimization problem $= 100$. For low pass and high pass filter, cut off frequency (normalized) is taken as 0.7 and 0.3, respectively. For band pass and band stop filters, lowest and highest edge frequencies (normalized) are 0.3 and 0.7. Population size for this design procedure is taken as 20. For PSO optimization, personal learning and cognitive acceleration coefficient is considered to be equal to 2. Bat parameters are taken as: Loudness is 0.5; pulse rate is 0.5; minimum and maximum frequency

is 0 and 2, respectively. In case of seeker, optimization parameters are as follows: minimum and maximum membership degree is given as 0.1 and 0.4; minimum and maximum frequency is 0.2 and 0.6, respectively.

Figures 1, 2, 3, and 4 compare the magnitude responses of actual filter and the filters projected with PSO, Bat, and seeker optimization algorithms for FIR—low pass, high pass, band pass and band select filters successively.

Figures 5, 6, 7, and 8 depict a comparison of convergence profile, i.e., the error function for FIR-LP, FIR-HP, FIR-BP, FIR-BS filters consecutively.

Tables 1, 2, 3, and 4 successively present the various other comparative outcomes of performance parameters of all techniques for 40th order FIR—low pass, high pass, band select, and band reject filters. Almost lowest reject band obstacle and select band ripple is achieved for seeker optimization algorithm while designing all the kinds of filters. For low pass, high pass, select band, reject band filters seeker
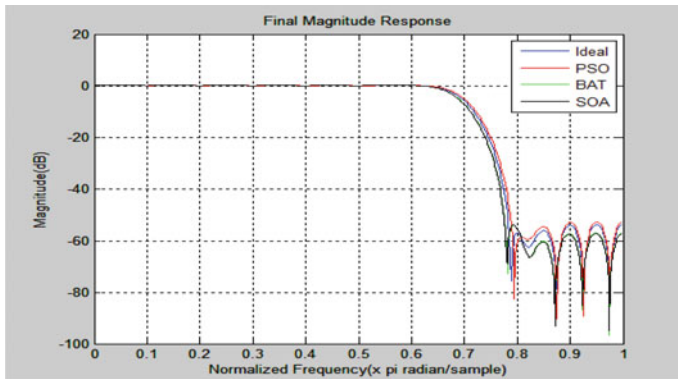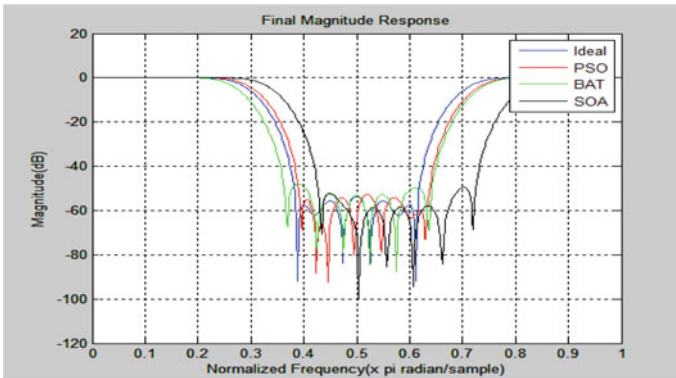

Fig. 1 Comparison of actual filter and filter projected with PSO, Bat, and seeker algorithm for low pass filter
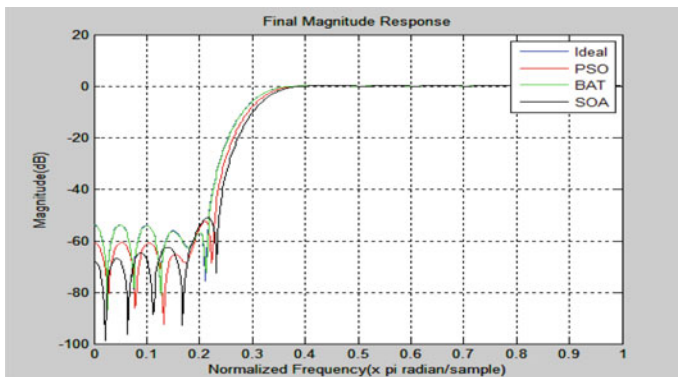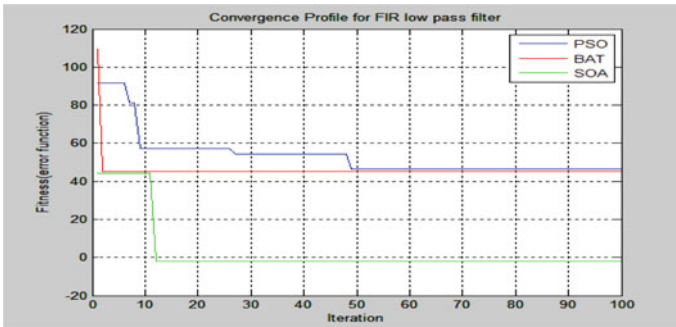

Fig. 2 Comparison of actual filter and filter projected with PSO, Bat, and seeker algorithm for high pass filter
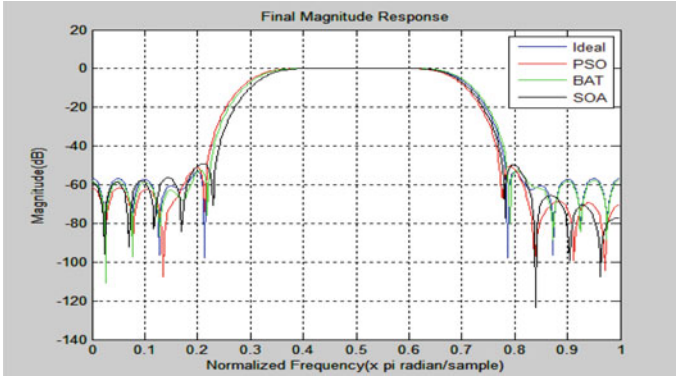
Fig. 3 Comparison of actual filter and filter projected with PSO, Bat, and seeker algorithm for band pass filter

Fig. 4 Comparison of actual filter and filter projected with PSO, Bat, and seeker algorithm for band stop filter

Fig. 5 Evaluation of convergence profile for low pass filter using PSO, Bat, and seeker

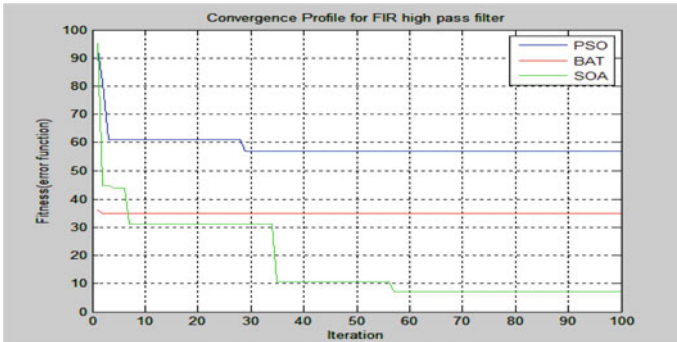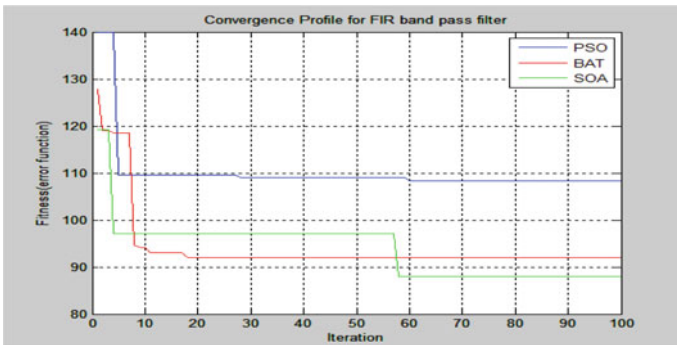**Fig. 6** Evaluation of convergence profile for high pass filter with PSO, Bat, and seeker

Fig. 7 Evaluation of convergence profile for band select filter using PSO, Bat, and seeker
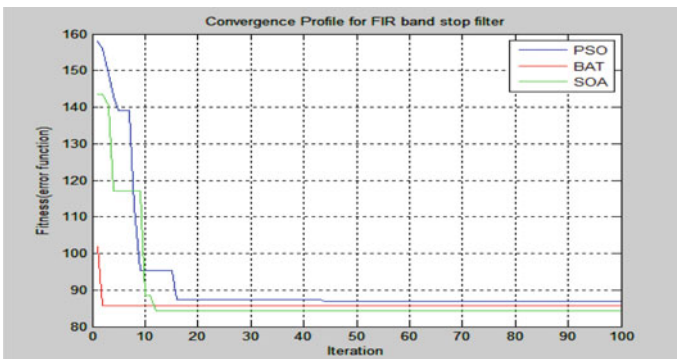

Fig. 8 Evaluation of convergence profile for band reject filter using PSO, Bat, and seeker

Table 1 Analysis of comparative variables for FIR-LP filter projected with various techniques

Technique	Max reject band attenuation(dB)	Max select band ripple	Max reject band ripple	Error fitness
PSO	−52.5	0.0027	0.002322	46.26
BAT	−53.76	0.0029	0.002053	45.17
SEEKER	−53.76	0.0029	0.002051	−2.006

Table 2 Analysis of comparative variables for FIR-HP filter projected with various techniques

Technique	Max reject band attenuation(dB)	Max select band ripple	Max reject band ripple	Error fitness
PSO	−53.12	0.0028	0.002208	56.96
BAT	−53.73	0.0029	0.002053	34.96
SEEKER	−53.73	0.0029	0.00201	7.18

Table 3 Analysis of comparative variables for FIR-BP filter projected with various techniques

Technique	Max reject band attenuation(dB)	Max select band ripple	Max reject band ripple	Error fitness
PSO	−49.71	0.0056	0.003268	108.4
BAT	−9.87	0.0044	0.002461	92.02
SEEKER	−52.18	0.0061	0.003426	87.9

Table 4 Analysis of comparative variables for FIR-BS filter projected with various techniques

Technique	Max reject band attenuation (dB)	Max select band ripple	Max reject band ripple	Error fitness
PSO	−52.97	0.0019	0.002241	86.96
BAT	−53.73	0.005	0.002059	85.71
SEEKER	−53.73	0.9997	0.003353	84.4

technique presents lowermost, or near to lowest reject band ripples of 0.002051, 0.00201, 0.003426, and 0.003353, respectively. Seeker design converges to the least value of error fitness value among all techniques. For low pass, high pass, band pass and band stop filter, it converges to min error count of −2.006 in 11, 7.18 in 57, 87.9 in 58 and 84.4 in 12 iterations. Thus, it performs best among all the design approaches discussed in this works

Statistical parameters of FIR filters obtained by the projection procedure for all the variant optimization algorithms are given in Tables 5, 6, 7, and 8 successively.

Table 5 Statistical data for FIR low pass filter with variant algorithms

Algorithm	Select band ripple				Reject band attenuation (decibels)			
	Max	Average	Variance	S D	Max	Average	Variance	SD
PSO	0.0027	0.001	0.000000776	0.000881	−52.5	−54.086	6.40958	2.531715
BAT	0.0029	0.001614	0.000003481	0.00059	− 53.76	−54.954	2.41288	1.553345
SOA	0.0029	0.002414	0.0000000881	0.000297	− 53.76	−57.2325	7.588291667	2.754685

Table 6 Statistical data for FIR high pass filter with variant algorithms

Algorithm	Select band ripple				Reject band attenuation (decibels)			
	Max	Average	Variance	SD	Max	Average	Variance	SD
PSO	0.0028	0.002486	0.000000048095	0.000219	−53.12	−58.176	10.48643	3.238276
BAT	0.0029	0.001867	0.0000002667	0.000516	−53.73	−54.938	2.46017	1.568493
SOA	0.0029	0.001643	0.0000003329	0.000577	−53.73	−54.938	2.46017	1.568493

Table 7 Statistical data for FIR band pass filter with variant algorithms

Algorithm	Select band ripple				Reject band attenuation (decibels)			
	Max	Average	Variance	SD	Max	Average	Variance	SD
PSO	0.0056	0.005	0.00000063	0.000794	−49.71	−58.1544	26.0031278	5.099326
BAT	0.0044	0.0039	0.0000003333	0.000577	−9.87	−53.1988	332.4233268	18.23248
SOA	0.0061	0.005433	0.0000009733	0.000987	−52.18	−59.4488	25.94118393	5.093249

Table 8 Statistical data for FIR band reject filter with variant algorithms

Algorithm	Select band ripple				Reject band attenuation (decibels)			
	Max	Average	Variance	SD	Max	Average	Variance	SD
PSO	0.0019	0.0014	0.0000001533	0.000392	−52.97	−55.7717	11.43669	3.381819
BAT	0.005	0.003422	0.000001701920	0.001305	−53.73	−57.6767	35.29782667	5.941197
SOA	0.9997	0.749125	0.248754	0.498753	−53.73	−57.6767	35.29783	5.941197

4 Conclusion

In the present article, the projection procedure of FIR digital filters is presented with the aim to diminish the error function by optimizing the variant filter parameters with the use of PSO, Bat, and seeker optimization techniques. The procedure runs for 100 iterations to minimize the error function by optimizing the filter coefficients. Different types of analysis are performed on the outcomes of the codes run on MATLAB environment such as statistical analysis, analysis of convergence profile and magnitude response analysis, and comparison of the variant parameters of filters, namely ripples, attenuation, and as forth. Comparison is performed between the PSO, Bat, and seeker optimization, and seeker optimization presents the best outcomes in terms of all the criterions.

References

1. Ababneh JI, Bataineh MH (2008) Linear phase FIR filter design using particle swarm optimization and genetic algorithms. Dig Sig Proc 18(4):657–668
2. Abdel-Rahman EM, Ahmad AR, Akhtar S (2012) A metaheurisic bat- inspired algorithm for full body human pose estimation. In: Ninth Conference on Computer and Robot Vision, pp 369–375
3. Aggarwal A, Rawat TK, Upadhyay DK (2015) Design of optimal digital FIR filters using evolutionary and swarm optimization techniques. Int J Electron Commun 70(4):373–385
4. Alam SM, Hasan MT (2010) Performance analysis of FIR filter design by using optimal, blackman window and frequency sampling methods. Int J Electr Comput Sci 10(1):13–18
5. Antoniou A (n.d.) Digital filters: analysis and design. McGraw Hill, New York
6. Shenoi BA (2006) Introduction to digital signal processing and filter design. Wiley, Canada
7. Coulombe S, Dubois E (1996) Multidimensional windows over arbitrary lattices and their application to FIR filter design. In: Proceeding IEEE international conference on acoustics, speech and signal processing. Atlanta, GA, pp 2383–2386
8. Dai C, Chen W, Zhu Y (2006) Seeker optimization algorithm. In: International conference on computational intelligence and security. Guangzhou, pp. 225–229
9. Dai C, Chen W, Zhu Y (2010) Seeker Optimization algorithm for digital IIR filter design. IEEE Trans Industr Electron 57(5):1710–1718
10. Dai C, Chen W, Zhu Y, Zhang X (2009) Seeker optimization algorithm for optimal reactive power dispatch. IEEE Trans Power Syst 24(3):1218–1231
11. Du ZY, Liu B (2012) Image matching using a bat algorithm with mutation. Appl Mech Mater 203(1):88–93
12. Gholami A, Ansari HR (2017) Estimation of porosity from seismic attributes using a committee model with bat-inspired optimization algorithm. J Petrol Sci Eng 152(2):238–249
13. Harris FJ (1978) On the use of windows for harmonic analysis with the discrete fourier transform. Proc IEEE 66(1)
14. Ifeachor E, Jervis B (2002) Digitalm signal processing: a practical approach. Pearson, UK
15. Jaddi NS, Abdullah S, Hamdan AR (2015) Optimization of neural network model using modified bat-inspired algorithm. Appl Soft Comput 37(C):71–86
16. Karaboga N (2005) Digital IIR filter design using differential evolution algorithm. J Adv Sig Proc 8(4):1269–1276
17. Karaboga N, Cetinkaya B (2006) Design of digital FIR filters using differential evolution algorithm. Circ Syst Sig Proc 25(5):649–660

18. Kennedy J, Eberhart R (1995) A new optimizer using particle swarm theory. In: Proceeding IEEE sixth international symposium on micro machine and human science. Nagoa, Japan, pp 39–43
19. Kennedy J, Eberhart R (1995) Particle swarm optimization. Proceeding IEEE international conference on neural networks. Perth, pp 1942–1948
20. Lemma TA, Bin Mohd Hashim F (2011) Use of fuzzy systems and bat algorithm for energy modelling in a gas turbine generator. In: IEEE colloquium on humanities, science and engineering, pp 305–310
21. Litwin L (2000) FIR and IIR digital filters. IEEE Potentials, pp 28–31.
22. Liu G, Li YX, He G (2010) Design of digital FIR filters using differential evolution algorithm based on reserved gene. In: Proceedings of the IEEE conference on evolutionary computation. Barcelona, Spain, pp 1–7
23. Liu G, Li YX, He G (2010) Design of digital FIR filters using differential evolution algorithm based on reserved gene. In: IEEE Conference on Evolutionary Computation. Barcelona, Spain, pp 1–7
24. Najjarzadeh M, Ayatollahi A (2008) FIR digital filters design: particle swarm optimization utilizing LMS and minimax strategies. In: IEEE international symposium on signal processing and information technology. Sarajevo, Bosnia and Herzegovina, pp 129–132
25. Nayak MR, Nayak CK, Rout PK (2012) Application of multi-objective teaching learning based optimization algorithm to optimal power flow problem. In: 2nd International conference on communication, computing and security, pp 255–264
26. Parks TW, Burrus CS (1987) Digital filter design. Wiley, New York
27. Parks TW, McClellan JH (1972) Chebyshev approximation for non-recursive digital filters with linear phase. IEEE Trans Circ The 19(2):189–194
28. Proakis JG, Manolakis DG (2000) Digital signal processing-principles, algorithms and applications. Prentice-Hall, New Delhi, India
29. Proakis J, Ingle V (2011) Digital signal processing using MATLAB, 3rd edn. Cengage, USA
30. Rao RV, Savsani VJ, Vakharia DP (2011) Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput Aided Des 43(3):303–315
31. Severino AG, Linhares LL, DeAraujo FM (2015) Optimal design of digital low pass finite impulse response filter using particle swarm optimization and bat algorithm. In: 12th international conference on informatics in control, automation and robotics, pp 207–214
32. Singh R, Verma HK (2014) Teaching-learning-based optimization algorithm for parameter identification in the design of IIR filters. J Inst Eng 94(4):285–294
33. Slowik A, Bialko M (2007) Design of IIR digital filters with non-standard characteristics using differential evolution algorithm. Bullet Pol Acad Sci Tech Sci 55(4):359–363
34. Tamiru AL, Hashim FM (2013) Application of bat algorithm and fuzzy systems to model energy changes in a gas turbine. Stud Comput Intell 427:685–719
35. Yang XS (2010) A new metaheuristic bat-inspired algorithm. Nat Insp Cooperat Strateg Optim 284(2):65–74
36. Yang XS, Deb S (2010) Eagle strategy using L´evy walk and firefly algorithms for stochastic optimization. Stud Comput Intell 284:101–111