Particle Swarm Optimization – based Digital FIR Filter design

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***Abstract*—Digital filters are integral to digital signal processing, separating signals contaminated by interference and restoring distorted ones. Finite Impulse Response (FIR) filters, outperforming IIR filters with stable frequency and linear phase response, pose multi-modal optimization challenges. These issues find solutions in optimization methods like Particle Swarm Optimization (PSO) and Improved Cuckoo Search Algorithm, aiming to minimize errors between actual and ideal responses. PSO, a stochastic bio-inspired optimization approach with straightforward implementation and parameter-controlled convergence, excels in multidimensional optimization amidst complex search spaces. This study employs the Kaiser Window Function to design a MATLAB-based digital band-pass FIR filter, optimizing it with PSO. Robustly comparing PSO and Improved Cuckoo Search Algorithm (ICSA), the results highlight the superior performance of the PSO-designed FIR filter across the frequency spectrum.**

Keywords—Finite Impulse Response Filter (FIR), Particle Swarm Optimization (PSO), Improved Cuckoo Search Algorithm, Kaiser Window Function, Digital Signal Processing.

I. INTRODUCTION

Filters are an essential component of signal processing, and they play a crucial role in shaping and analyzing various types of signals. A filter is a mathematical formula or circuit designed to examine a signal by picking and choosing which frequency components to change. They are employed in many applications, including audio processing, image processing, and communication systems. Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters are two types of digital filters. FIR filters have a finite impulse response and offer greater stability and linearity in phase response in contrast to IIR filters.

The designing of FIR filters includes conventional windowing and frequency sampling methods. The windowing method involves the selection of various windows, such as Kaiser, Hamming, Hanning, Bartlett, Rectangular, etc. These conventional techniques often produce inadequate results and hence optimization is required. The optimization technique involves adjusting various parameters of the FIR filter to come to a stable frequency response, linear phase, and improved filter coefficients. The main aim is to reduce the greatest deviation from the ideal and actual response. These optimization methods comprise of Genetic Algorithm, Artificial Bee Colony Algorithm, Cuckoo Search Algorithm (CSA), PSO algorithm, etc. PSO is a powerful optimization algorithm that is appropriate for digital filter design due to its simplicity, fast convergence, ability to optimize non-differentiable cost functions, and suitability for multi-objective optimization. PSO is based on the intelligence of swarm and learning. A metaheuristic optimization technique known as the enhanced CSA was the brood parasitic behavior of cuckoo birds. It incorporates Lévy flight behavior and a new dynamic parameter adaptation strategy to enhance its convergence speed and accuracy in solving complex optimization issues.

This paper is an attempt to construct a bandpass FIR filter with a stochastic method of PSO algorithm to produce enhanced coefficients of filters and a response that is close to an ideal response. The Kaiser window is kept as a reference for designing the filter and robust comparison is performed with ICSA. The outcomes indicate that the use of PSO in filter design yields better filter coefficients and significantly minimizes stop band ripples. It outperforms ICSA with respect to the frequency spectrum, providing a good balance between the ripples in the passband and stopband attenuation.

The paper henceforth is organized into six sections. In section II, related works are discussed. FIR filter modeling is presented in section III. Section IV is focused on the design methodologies which are compared. The simulation settings and the results concerning stopband attenuation are discussed in section V. The work has been concluded in section VI.

II. RELATED WORKS

The Kaiser window function constructs a digital FIR filter in [1], using the application of the particle swarm optimization technique to optimize the filter design. The findings of the simulation performed by the authors using MATLAB demonstrate that the designed FIR filter outperforms the previously designed FIR filter in accordance with the frequency spectrum. The study also highlights the effectiveness of combining the Kaiser window function and PSO in designing digital FIR filters. The work explained in this paper however was not sufficient and the need for more concrete knowledge was required which was fulfilled through [2] which suggests the design of FIR filters using three distinct techniques: the Hamming window, Kaiser Window, and equiripple techniques. Additionally, it introduces a 2D FIR filter and evaluates its output responses, highlighting its superior speed compared to conventional FIR filters employing various windowing techniques. The study also provides insights into the implementation and simulation of all these filter designs within the MATLAB and Simulink environments. The primary purpose of employing filters is to

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reduce the presence of noise within the data. To meet precise frequency specifications, higher-order filters become necessary. [3] was then utilized for a better understanding of filter modeling which suggests that during signal transmission through any medium, unwanted components, often referred to as noise, inevitably affect the signals. Finite Impulse Response (FIR) filters have gained popularity due to their advantages of minimal design complexity and lower hardware costs. Since there were a lot of optimization challenges that were faced while designing FIR filter through the Kaiser window, different optimization techniques have to be implemented like [4] where the author discusses that in the realm of digital signal processing and engineering, Finite Impulse Response (FIR) filters are widely favored due to their well-established attributes of strict stability and linear phase characteristics. Addressing the limitations of conventional methods for designing digital filters, this paper adopts the recently introduced Grey Wolf Optimization (GWO) algorithm. Furthermore, another algorithm [5] was utilized in which, the Ant Lion Optimization (ALO) technique is applied to the design of FIR bandpass and band stop filters (BPF and BSF) with an order of 20. ALO draws inspiration from the interaction between ants and antlions, employing a five-step hunting mechanism. These steps involve ants' random movement, trap construction, and capture in the antlion's hole, sliding ants toward the trap's center, capturing the prey, and hole reconstruction. ABC algorithm is a very modern and robust algorithm that is similar to bio-inspired algorithms such as PSO and in [6] author stresses that the precise design of Finite Impulse Response (FIR) filters holds significant importance. Consequently, this paper presents an enhanced version of the Artificial Bee Colony algorithm Notably, these filters exhibit minimal ripple in both the passband and stopband, maintain flat amplitude, and demonstrate excellent attenuation characteristics. Different algorithms knowledge is necessary for better understanding and thus [7] investigates that the paper leverages the Honey Badger Algorithm (HBA) to optimize the coefficients of FIR linear phase filters, including Band Pass Filter (BPF), Band Stop Filter (BSF), Low Pass Filter (LPF), and High Pass Filter (HPF). HBA efficiently computes the optimal coefficients for the specified filter through its digging and honey-searching modes. Consequently, this research achieves superior frequency performance characteristics, characterized by maximum stopband attenuation and minimal passband ripple. It was also seen that extensive knowledge of different algorithms will help to understand more. Now CSA is being checked in [8] where the paper presents a novel method for designing even-order low-pass FIR filters and odd-order bandpass FIR filters using an adaptive Global Best-steered Cuckoo Search Algorithm (gbest CSA) to optimize coefficients based on mean square error. Comparative evaluations against standard CSA and Parks McClellan algorithm demonstrate the superior efficacy of the proposed approach. To gain a better understanding with respect to the previous paper, [9] was utilized where it showcases a comparative investigation into the design of high-order Type 2 low-pass FIR filters using the Cuckoo Search Algorithm (CSA), Gravitational Search Algorithm (GSA), and Artificial Bee Colony (ABC) algorithm. CSA exhibits swifter global convergence across diverse FIR filter design scenarios, outperforming GSA and ABC in terms of stop-band attenuation (As) and pass-band ripple (Rp). Specifically, in the case of order 79, CSA achieves a 7.89% improvement in stop-band attenuation and a 9.43% enhancement in pass-band ripple compared to the Parks and McClellan algorithm However, as filter length increases, so does the number of adders and multipliers, particularly affecting filter performance due to multipliers' slower processing. This is explained in [10] By implementing Booth Multipliers and carrying select adders in a 15-tap FIR filter design using Verilog HDL and Xilinx Vivado tools, this study reduces both area and delay while improving power efficiency—making it suitable for low-voltage and low-power VLSI applications. The need to learn about PSO and its attributes was felt. Thus [11] addresses the intricate task of designing digital filters with multiple, often conflicting, criteria. The primary objective is to identify the optimal filter configuration, which cannot be efficiently achieved through simple iterative methods. Instead, an optimization-based approach, utilizing Particle Swarm Optimization and dynamic adjustable PSO (DAPSO) for low-pass finite impulse response (LPFIR) filter design, is discussed. DAPSO, an enhanced version of PSO, introduces improvements in swarm updating and velocity vectors, thereby enhancing solution quality. Some application was also discussed in [12] proposing an enhanced particle swarm optimization algorithm, inspired by firefly position optimization, to overcome local optima and improve convergence speed. This algorithm, equipped with adaptive inertia weights, flight factors, chaos, and mutation strategies, optimizes FIR digital filters effectively. Simulations confirm its superior convergence speed and precision. Authors in [13] modified PSO parameters. They claimed in their article that the greatest optimization technology is particle swarm optimization. It turned out to be a very promising tool for optimization. Now, it was time for some application analysis of the algorithm thus [14] introduces a novel blind adaptive equalizer, termed BEPC-PSO, which employs a particle swarm optimization (PSO) based training algorithm with a polynomial cost function. Unlike conventional methods relying on symbol modulus, BEPC-PSO automatically recovers the carrier phase and exhibits enhanced performance. Simulations conducted on a finite impulse response (FIR) voice band channel demonstrate BEPC-PSO's superior convergence rate and reduced inter-symbol interference (ISI), resulting in significantly improved equalization efficiency compared to other blind equalizers. Further, expanding this [15] presents a novel approach utilizing Minor Component Analysis (MCA) neural learning and fractional derivatives (FD) to design digital Finite Impulse Response (FIR) filters. The method models the design problem as an integral error summation in the frequency domain, resolved using MCA neural learning. Fractional derivatives are applied for improved frequency response, and Particle Swarm Optimization is employed to optimize Fractional Derivative Constraints (FDCs). Comparative analysis with recent results underscores the effectiveness of this approach. Finally, at last, its whole analysis was done based on [16] where it tackles communication between a multi-antenna Base Station and a single-antenna user aided by an Intelligent Reflecting Surface. It optimizes beamforming at both ends without Channel State Information, employing a Particle Swarm Optimization method to minimize power while maintaining a minimum signal-to-noise ratio. Results indicate comparable performance to CSI-based beamforming.

Thus, there are many contributions related to the study of PSO and ICSA which are listed as,

- The potential contribution of the work lies in conducting a detailed comparison between Particle Swarm Optimization (PSO) and Improved Cuckoo Search Algorithm (ICSA) for FIR filter design.
- By assessing factors such as stopband attenuation, and optimization efficiency, it aims to provide insights into the advantages of using PSO over ICSA in the context of constructing FIR filters, benefiting digital signal processing applications.

III. FIR Filter Design

A Finite Impulse Response filter generates a result using a linear combination of input values from the past and the present making use of a limited number of coefficients. As a result, an FIR filter's output eventually reaches zero after a finite number of samples. Transfer function $H(z)$ of FIR filter can be characterized as,

$$H(z) = \sum_{n=0}^{N} h(n) z^{-n}, \quad (1)$$

which can further be written as,

$$H(z) = h(0) + h(1)z^{-1} + \cdots + h(n)z^{-N}, \quad (2)$$

where, $h(n)$ is impulse response at time instance n, and N is the order of the filter. The output of the filter in time domain, $y(n)$, and frequency domain, $Y(z)$, are respectively as given below,

$$y(n) = x(n) * h(n), \quad (3)$$

$$Y(z) = X(z) \times H(z), \quad (4)$$

where, $x(n)$ and $X(z)$ are the input signals of the time and frequency domain respectively. The frequency response of a one-dimensional FIR filter can be obtained by taking the Fourier transform of the filter coefficients $h(n)$ as follows,

$$H(w_k) = \sum_{n=0}^{N} h(n)\, e^{-jw_k n}, \quad (5)$$

where, k is ranging from 0 to N-1. The sampling of frequency is done with N points of the range [0, π].

When signal processing is applied to smooth out or analyze a signal, a Kaiser window is applied as a weighting function. Digital signal processing is frequently used in applications like Fourier analysis and digital filtering. The constant value of the Kaiser window is one inside a predetermined range and 0 outside that range. The coefficients of the Kaiser window are calculated using:

$$w(n) = \frac{I_0\left(\beta\sqrt{1-\left(\frac{n-\frac{N}{2}}{\frac{N}{2}}\right)^2}\right)}{I_0(\beta)}, \quad (6)$$

where, I_0 is 0th order modified Bessel function.

$$I_0 = 1 + \sum_{k=1}^{\infty}\left[\frac{(x/2)^2}{k!}\right]^2 \quad (7)$$

where the parameter β controls the relative sidelobe attenuation. The value of β should be appropriately chosen to achieve the desired main-lobe width and side-lobe attenuation.

IV. Design Methodologies

This section discusses design techniques, where the FIR filter is designed using the PSO and ICSA algorithms, and a robust comparison is made.

A. PSO Algorithm

PSO is a population-based metaheuristic optimization technique inspired by the social behavior of birds' flock or a school of fish. It adjusts each particle's position and velocity in accordance with the most effective solution discovered by it and its neighbors to determine the ideal solution using a swarm of particles (representing a potential solution). The algorithm for PSO is given below in Fig.1,

Step I. Prescribe parameters of filter, error fitness function, and swarm size and set the boundaries for the search space.

Step II. Initialize particles to random positions and velocities in the search space.

Step III. Enumerate fitness function value.

Step IV. Update local and global best fitness value.

Step V. Reanalyze the fitness value and compare it with its $Pbest_i$ and $Gbest$.

Step VI. Repeat steps II through V repeatedly until the required number of iterations has been reached.

Step VII. The outcome is a set of optimized filter coefficients.

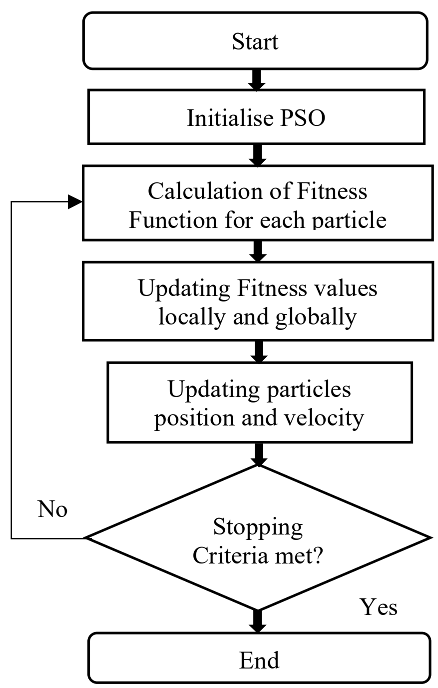

Fig.1. Flowchart of PSO algorithm

The current velocity vector, and position vector is kept as,

$$v_i = [v_{i1}, v_{i2}, v_{i3}, \dots\dots\dots, v_{iD}], \quad (8)$$

$$x_i = [x_{i1}, x_{i2}, x_{i3}, \dots\dots\dots, x_{iD}], \quad (9)$$

where, D defines the number of dimensions. The velocity of every particle is updated according to eq. (10) as shown below,

$$V_i^{n+1} = w * i * V_{iD} + c_1 * rand1 * (P_{best} - X_{iD}) + c_2 * rand2 * (G_{best} - X_i), \quad (10)$$

where, V_{id} defines the particle's velocity in d-dimension, X_{id} is the current particle position (solution) in d-dimension, w is the weight of inertia that prevents the particle from abruptly changing the direction, $rand1$ and $rand2$ are functions which are random in the range [0,1]. The parameters c_1 and c_2 are the cognitive and social learning factors. Further, the position of each particle will be updated as follows,

$$X_i^{n+1} = X_{iD} + V_i^{n+1}. \quad (11)$$

Using equations (10) and (11) the particle Pi follows its own best, i.e., personal best-called $Pbest_i$ and reach up to the position of global best, $Gbest$. The personal best for i-th iteration ($Pbest_i$) and the global best ($Gbest$) are given by,

$$Pbest_i = \{pb_{i1}, pb_{i2}, pb_{i3}, \ldots, pb_{iD}\}, \quad (12)$$

$$Gbest = \{gb_1, gb_2, gb_3, \ldots, gb_D\}. \quad (13)$$

B. *ICSA Algorithm*

The CSA is a nature-inspired optimization method that simulates the reproduction behaviour of cuckoo birds. Levy flights and random walks develop fresh solutions, which are then assessed over a fitness function. The worst solutions are replaced by new ones using a replacement strategy. Within a specific range $(1 < \lambda < 3)$, the likelihood of obtaining food is influenced by the duration of each step. The $Levy\ (\lambda)$ distribution function gives the step length of Levy Flight well known as random walk and the equation is given by,

$$Levy\ (\lambda) = \left| \frac{\Gamma(1+\lambda) \times sin\ (\pi\lambda/2)}{\Gamma((1+\lambda)/2) \times \lambda \times 2^{\left(\frac{\lambda-1}{2}\right)}} \right|^{1/\lambda}, \quad (14)$$

and cuckoos pursue the postulate of Lévy flight when they lay eggs in random fashion where a new nest is generated.

$$x_i^{t+1} = x_i^t + \alpha 1 \oplus Levy\ (\lambda), \quad (15)$$

'$\alpha 1$' stands for step size where ($\alpha 1$>0) and '$\oplus$ 'represents entry wise multiplication. An improved search can be acquired with the help of levy flight where steps are derived from levy distribution function.

$$Levy \sim u = t^{-\lambda}, (1 < \lambda < 3), \quad (16)$$

CSA is predicated on three tenets motivated by the conduct of cuckoo birds:

- Every cuckoo dumps its eggs one by one inside the host birds' nest randomly, where each egg is conceived as a possible solution.
- The qualitative egg having higher fitness value shall be imparted to the subsequent generation.
- Host nests are fixed in number and the probability (Pa) that the host bird will detect a cuckoo egg remains within the boundary [0, 1].

The algorithm for ICSA can be given step-wise as Fig.2,
Step I. A population of host nest size n is initialized, denoted by x_i, where (i =1,2, n).
Step II. Find the function fitness value of F_i = f (x_i) for all x_i.
Step III. Until the stopping criteria is satisfied, do steps 4-7.
Step IV. Determine the cuckoo egg x_j fitness function F_j by randomly creating one from the host nest and applying Levy flight.
Step V. If ($F_i > F_j$) then swap out x_i with x_j and replace F_i with F_j.
Step VI. Abandon some nests that are worst and establish new ones at random, to make up for the lost nests.
Step VII. Keep the better ones and rate each solution to see which is now the most successful.
Step VIII. Results processing and visualization.

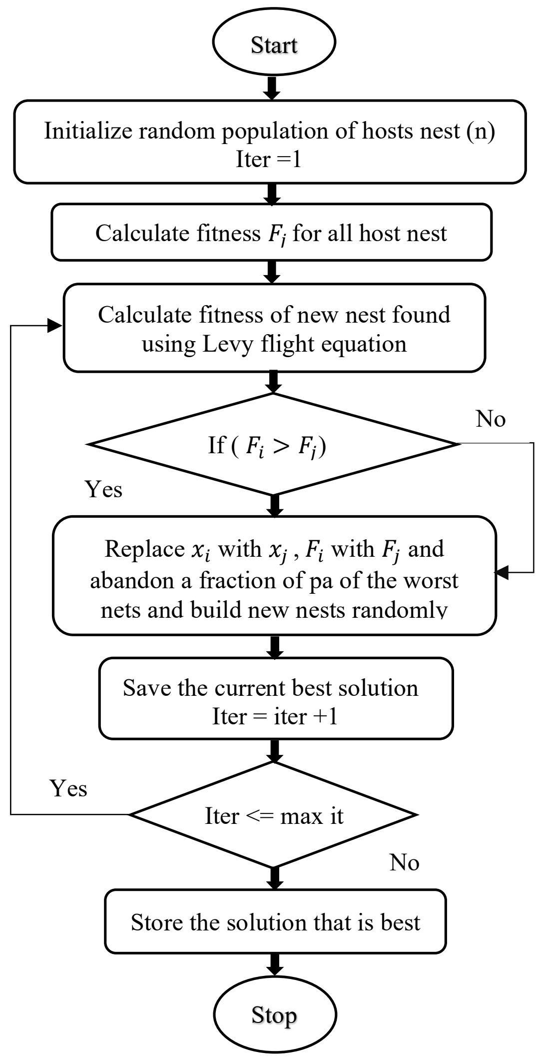

Fig. 2. Flowchart of ICSA algorithm

V. Simulation Results and Discussions

This section presents the findings from the analysis of the performance of the proposed system. The analysis was carried out using MATLAB R2021b on a system with an Intel(R) Core (TM) i5-1035 processor running at 1.00 GHz, 4 cores, and 8 logical processors.

The Kaiser window creates the FIR bandpass filter. The outcomes are measured in terms of frequency response and filter coefficients. The PSO algorithm is applied to the designed filter to obtain better filter coefficients and a better response. The simulations were carried out in MATLAB. The parameter beta (β) in the Kaiser window is taken as 8. The response of magnitude of FIR bandpass filter of order 31 with beta parameter as 8 is shown in Fig.3. Figure 4 displays the response of phase of an FIR bandpass filter designed using a Kaiser window. PSO Algorithm is applied to the designed FIR filter. The PSO design parameters are displayed in Table 1.

Table.1 suggests that the order of the filter is 31. The search space population size is 32. The inertia coefficient is kept as 0.3 The most iterations allowed is 1000 and is varied to get better results. The output response obtained by applying the PSO algorithm on the FIR filter of 31st order with a population size of 32 and 1000 iterations is as shown in Fig.5. The Table.2 suggests that the filter's order is 31. The population of search space has a size of 100. The alpha parameter is kept as 0.3. The probability function (pa) is assumed to be 0.01 and the step size is taken as 0.02 and is varied in accordance with the filter's order.

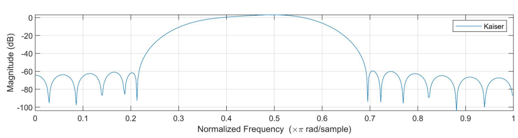

Fig.3. FIR Filter Magnitude Response of Order 31

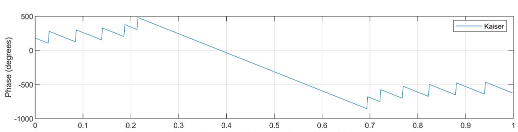

Fig.4. FIR Filter Phase Response of Order 31

TABLE 1. PARAMETERS OF PSO [1]

Parameters	PSO Value
Maximum Iteration	1000
Order	31
Population Size	32
w	0.3
w-damp	0.9999
c_1	2
c_2	2
Max. Position	1
Min. Position	-1
Max. Velocity	2
Min. Velocity	-2

TABLE 2. PARAMETERS OF ICSA [9]

Parameters	ICSA Value
Order	31
Population	100
Alpha	0.3
Pa	0.01
Step size	0.02

The filter's output response, designed using the ICSA algorithm, is displayed in Fig.6. The pass band frequencies (wp1 and wp2) and stopband frequencies (ws1 and ws2) are fixed at (0.4π rad/s and 0.5π rad/s) and (0.38π rad/s and 0.53π rad/s) respectively. The PSO produces a series of optimized filter coefficients that are displayed in Table.3. The output of the FIR filter utilized by PSO performs better when it comes to stop band ripples and cutoff responsiveness as the population size and number of iterations rise in tandem. The stop band ripples significantly diminish. Moreover, a desired sharp cutoff response is shown when numerous repetitions are increased. Stop band attenuation is examined between the outcomes from PSO and ICSA. The stop band attenuation describes how much the frequency components in the stop band, which is the frequency range that the filter is intended to suppress, are attenuated by the filter. In general, a higher stop band attenuation is better for an FIR filter, as it indicates that the filter can better suppress unwanted frequency components in the stop band (As). Table.4 shows the Performance comparison between PSO and ICSA. It demonstrates that the values with respect to stop band attenuation obtained from PSO are superior to ICSA. With respect to stop band attenuation, it can be summarized that the ICSA algorithm is outperformed by PSO. It is crucial to remember that numerous variables, including the size, complexity, and optimization criteria of the problem, might affect how well an optimization algorithm performs.

TABLE 3. OPTIMIZED FILTER COEFFICIENTS GENERATED BY PSO

h(n)	Filter Coefficient using PSO
h(1) = h(32)	0.000703056471845588
h(2) = h(31)	0.000399945106867841
h(3) = h(30)	-0.00657793454015004
h(4) = h(29)	-0.00405505205439041
h(5) = h(28)	0.0163839500061333
h(6) = h(27)	0.00965277305066264
h(7) = h(26)	-0.0212426429781287
h(8) = h(25)	0.000217350689658324
h(9) = h(24)	0.0189603064385656
h(10) = h(23)	-0.0514762349652740
h(11) = h(22)	-0.0310222392986041
h(12) = h(21)	0.143110687095683
h(13) = h(20)	0.0859275288129647
h(14) = h(19)	-0.225906522954189
h(15) = h(18)	-0.174651296308995
h(16) = h(17)	0.239270282015608

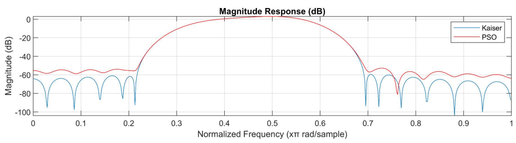

Fig.5. PSO Magnitude response

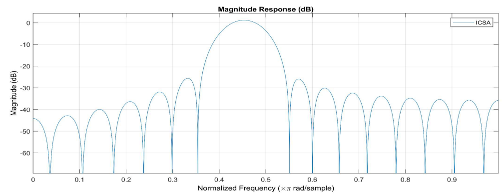

Fig.6. ICSA Magnitude response

TABLE 4. PERFORMANCE COMPARISON BETWEEN PSO AND ICSA

N	Method	As (dB)
29	**PSO**	42
	ICSA	13
31	**PSO**	49
	ICSA	14
51	**PSO**	43
	ICSA	18
71	**PSO**	38
	ICSA	21
91	**PSO**	42
	ICSA	25

VI. CONCLUSION

The FIR bandpass filter is built using the Kaiser Window function. The FIR filter is subjected to the PSO algorithm. By providing a unique mechanism for updating the swarm's position and velocity, it is evident that the PSO technique improves the solution qualities. The findings show that the PSO technique produces an optimized set of filter coefficients that ultimately improves response and decreases stop band ripples. When the results of PSO were compared with ICSA, it was discovered that PSO had better stopband attenuation as the objective function. With the use of the Kaiser window function and the MATLAB simulation tool, an effective FIR filter is designed. The outcomes portray that the constructed FIR filter outperforms the FIR filter that was designed using ICSA and also the conventional methodologies used for constructing FIR filters regarding the frequency spectrum. It is discovered that the ripples of the stop band decrease significantly. It is also noted that a favourable response is obtained with an increase in iterations.

The paper discusses PSO as a suitable optimization technique but doesn’t delve into the details of parameter tuning. Optimizing the PSO parameters can significantly impact its performance, and not addressing this aspect can be a limitation. The study also mentions the superiority of the FIR filter optimized with PSO over ICSA but doesn't specify the evaluation metrics used. Consideration of real-time implementation and hardware constraints is crucial. Research could focus on optimizing filter designs for real-time applications, where low latency and efficiency are critical.

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