DOI 10.15622/ia.22.3.7

R. SHARMA, K. SHARMA, T. VARMA

DESIGNING OF 2D-IIR FILTER USING A FUSED ESMA-PELICAN OPTIMIZATION ALGORITHM (FEPOA)

Sharma R., Sharma K., Varma T. **Designing of 2D-IIR Filter Using a Fused ESMA-Pelican Optimization Algorithm (FEPOA).**

Abstract. Many Digital Signal Processing (DSP) applications and electronic gadgets today require digital filtering. Different optimization algorithms have been used to obtain fast and improved results. Several researchers have used Enhanced Slime Mould Algorithm for designing the 2D IIR filter. However, it is observed that the Enhanced Slime Mould Algorithm did not achieve a better solution structure and had a slower convergence rate. In order to overcome the issue a fused ESMA-pelican Optimization Algorithm (FEPOA) is utilized for designing the 2D IIR filter which incorporates the pelican Optimization Algorithm with the Enhanced slime Mould Algorithm (ESMA). At first, the Chaotic Approach is utilized to initialize the population which provides the high-quality population with excellent population diversity, after that the position of population members is to identify and correct the individual in the boundary search region. After that, by the pelican Tactical Approach is to examine the search space and exploration power of the FEPOA, then the Fitness is calculated randomly, and the best solution will be upgraded and then moved towards the iterations. It repeats the FEPOA phases until the execution completes. Then the best solution gives the optimal solution, which enhances the speed of convergence, convergence accuracy and the performances of FEPOA. The FEPOA is then implemented in the IIR filter to improve the overall filter design. The results provided by FEPOA accomplish the necessary fitness and best solution for 200 iterations, and the amplitude response will achieve the maximum value for =2,4,8 as well as the execution time of 3.0158s, which is much quicker than the other Genetic Algorithms often used for 2D IIR filters.

Keywords: FEPOA, IIR filter, population member, FIR filter, Chaotic approach, Pelican's tactical approach.

1. Introduction. Digital filters are a fundamental component of digital systems because they filter recorded signals in DSP, which artefacts and sound might taint. DSP and allied fields like multimedia content analysis and digital transportation have extensively used and placed a high value on digital filters. On the other hand, the drawbacks and issues with creating such filters have prompted researchers to abandon conventional design methods in favor of time and money-saving, cost-effective solutions. The impulse response length often separates digital filtering into two categories: Finite Impulse Response (FIR) and Infinite Impulse Response (IIR). IIR filtering systems are used more frequently than analogous FIR systems because they have a smaller group delay, lower computational cost (less order), and considerably higher and better accuracy in satisfying the performance criteria [1]. On the other hand, because the IIR filter has feedback, the impulse response has an indefinite length [2]. Because its transfer function contains poles, the construction of an IIR filter has proven to be difficult. An IIR transfer method's phase response becomes nonlinear, and its magnitude response drifts due to the quantized correlation coefficients of the denominator coefficients, which leads to instability. As a result, multiple efforts were undertaken to utilize various optimization techniques to provide the best possible filter response [3]. Dealing with their stability limitations is one of the key challenges in their optimal designs, as there are no needed and adequate convex stability situations for filters of a higher order [4]. Various scholars have described various algorithms in recent years to handle optimization challenges. Some of them have been given here in common. A population-based method called Harmony Search (HS), which draws inspiration from music, has effectively solved global optimization issues [5]. A hybrid optimization method, which integrates the Moth Flame Optimization (MFO) methodology, as well as the Variable Neighbor Search (VNS) heuristic, has also been developed for an Infinite Impulse Response (IIR) filter [6]. A hybrid technique called the P Norm Optimization and ANN are combined or integrated for Auto Adaptive IIR Filter [7]. Invasive Weed Optimization (IWO) is a meta-heuristic technique that is used in the research to construct an order eight high-pass filter with Infinite Impulse Response (IIR) [8]. A Differential Evolution technique that combines polar and rectangular coordinates has been used for IIR Filter [9]. A digital filter with IIR was created using the hybrid optimization methodology and employed with the Dynamic-Static Topology of Particle Swarm Optimization (DS-PSO) method [10]. The system of roughly linear-phase recursive digital filters is explored using a constrained optimization approach. The concept is based on limited optimization techniques for IIR digital filters with nearly linear stages [11]. A bio-inspired meta-heuristic Biogeography-Based Optimization (BBO) process is used for IIR Filter. This algorithm mimics various species' migration and mutation processes, allowing habitat structures. [12]. A new metaheuristic technique called Average Differential Evolution with Local Search (ADE-LS) has been developed and used to find unidentified IIR devices [13]. These are some of the algorithms used for the IIR filter design. Over the past few decades, the formulation and usage of metaheuristics to solve optimization problems have become prominent. A wide range of research investigations has been recently sparked by formulating practical optimization issues and their effective resolution using metaheuristic algorithms [14]. The Contribution of the Paper is enumerated as:

– The Pelican Optimization Method and ESMA are combined to create a hybrid algorithm, which improves performance by speeding up convergence, increasing convergence rate, and improving convergence precision.

– The population is initialized using a chaotic technique. Then using a pelican's tactical strategy, each member of the population is located and transported toward the area that was found to correct them to the boundary search region. Then all the updating and iteration processes are performed, and the Fitness is randomly determined and identified. The best candidate solution is finally presented as the best answer.

The remainder of the paper is structured as follows: The relevant studies in earlier technology are described in Section II, the design of the 2D IIR filter is shown in Section III, the proposed method is listed in Section IV, the outcomes are reviewed in Section V, and the study is ended in Section VI.

2. Related works. Several types of research have been carried out for IIR Filters in digital signal processing. Some of the research has been analyzed in the following literature survey.

In study [15] the authors developed a metaheuristic algorithm, ESMA (Enhanced Slime Mould Algorithm). ESMA is an enhanced strategy of SMA. The proposed ESMA's efficient and exceptional performance has achieved the initially anticipated improvement in SMA. Although ESMA has performed exceptionally well, it still has certain flaws. As an illustration, ESMA's convergence precision is not always optimum. There is still an opportunity for the development of convergence accuracy. On the one hand, innovative tactics for improving ESMA's performance should be considered in future work. On the other hand, the suggested approach might address more optimization issues in more areas.

Study [16] proposed a parallel-pipeline-created finite impulse response (FIR) filter. FPGA device is used to implement the suggested IIR design. So in terms of signal processing, FIR-based IIR architecture is more appealing than selective. However, the digital filter's operating speed drops as the word length increases.

According to paper [17], constructing adaptive finite impulse response filters is a linear optimization technique, whereas designing adaptive IIR filters in the appearance of observation noise is a nonlinear optimization challenge. A mean square technique and a multi-innovation least mean square method are created for the IIR filters with AR noise, and their convergence is analyzed.

In paper [18] the authors proposed the computation of the unknown IIR filter's parameters in this research using a cutting-edge optimization method called the dragonfly algorithm (DA). The implemented dragonfly method obtains the minimal MSE value and estimates the system coefficients close to the actual value. Compared to BA, CSO, and PSO, the simulated outcomes imitate the procedure's effectiveness. Future problems involving identifying complicated and nonlinear systems can be solved using this technique.

Study [19] proposed the optimal design of IIR filters addressed in this study using two forms of ant colony optimization, the ant organization and the ant colony scheme. The pole positions utilizing optimal coefficients have demonstrated the stability of the developed filters. The lower MSE values are attained via the ACS algorithm.

In paper [20] the authors suggested a unique population-based optimization technique called the Firefly Algorithm (FA), which imitates the attraction and flashing behavior of fireflies, and has demonstrated promising results in treating global optimization issues. The empirical results demonstrate that IFA can stabilize global exploration with local exploitation. Compared to previous FA versions, it provides the best solutions – at least in terms of comparable outcomes for the bulk of the 12 global optimization issues. We also evaluate IFA's efficiency and efficacy by employing it to address well-known design problems with IIR filters. The experimental results and comparisons show that IFA outperforms various meta-heuristics in solution accuracy, resilience, and convergence rate.

In study [21] the authors proposed that Combining Joint Photographic Experts Group (JPEG) firmness is an adaptive approach. The ECG signal was fed through the approximately linear IIR filter to filter out noise from ECG measurements. The advantage of nearly-linear IIR filters over conventional IIR is that the pass-through signal filter is not distorted. With recent advancements, the JPEG compression method is now suitable for 1d signals with quality greater than 8 bits. It has also been optimized for microcontroller units (MCUs) with slow processing speeds. To reduce the degree of signal distortion after the filter, we can alter the number of overlap phases, although doing so would increase the delay and duration of the filter.

An analytical synthesis process creates lower zero/L2 sensitivity metrics relating to sparse standard state transformation function is suggested in this study for obtaining an ideal IIR state-space realization, or minimal pole-zero as well as pole-L2 sensitivity realizations, according to paper [22]. Strong robustness and a maximum of $4n + 1$ multiplications per output sample are features of the proposed nth-order realization that help it maintain computational efficiency while preventing output distortion and instability. The suggested approach might incorporate adaptive IIR filter design, parallel signal processing, multidimensional signal processing, and multi-input and multi-output (MIMO) signal processing.

Study [23] proposed an evolutionary technique to create reliable IIR filters for binaural audio equalization. The filters' second-order sections (SOSs) are arranged in a cascade, and the gravitational search algorithm (GSA) is employed. IIR filter stability was added as a restriction in this study. The problem may be rewritten in the coming years to include steadiness as a penalty term within the fitness function. Additional limitations or penalties may be required to prevent straightforward solutions like those presented in this research. Because the offered procedures are heuristic, the hyperparameters search can potentially be expanded by starting many batch tests to find improved results.

A brand-new technique for creating a reliable digital IIR filter in the frequency domain was put out by the authors [24]. The technique uses the Quantum PSO with artificial bee colony (ABC) algorithms, which improve performance in passband and stopband regions. By employing the novel discovery and replacement process of the scout bee from the ABC algorithm, the suggested method modifies the QPSO methodology. Although there is a slight rise in processing complexity, efficiency in terms of fidelity parameters is much enhanced.

We anticipated some of the difficulties ahead based on the studies mentioned above, which are listed below. From the above analysis, ESMA still has shortcomings in Convergence accuracy. In Parallel-pipeline based FIR filter, the digital filter's operating speed drops as the word length increases. On the JPEG compression approach, we can modify the number of overlap models to decrease the amount of signal distortion after the filter, but doing so would lengthen the filter's delay and duration. In Gravitational Search Algorithm (GSA), the IIR filter's stability was added as a restriction. In the hybrid QPSO and ABC algorithm, effectiveness in terms of fidelity constraints is greatly improved, albeit at the expense of slightly more complicated computation. A more efficient method should be suggested to address the drawbacks above, which are enumerated in the below segment.

3. Design of 2-D IIR filter. The structure of the Nth order 2-D IIR filter with the Transfer function can be written as:

$$H(z_1, z_2) = H_0 \frac{\sum_{i=0}^{N}\sum_{j=0}^{N} u_{ij} z_1^i z_2^j}{\prod_{k=1}^{N}(1+v_k z_1 + w_k z_2 + x_k z_1 z_2)}, u_{00} = 1, \tag{1}$$

where $\{ u_{ij}, v_{k,}, w_k, x_k \}$ are filter coefficients. Let the frequencies $\omega 1$, $\omega 2 \in [-\pi, \pi]$, $z_1 = e^{-j\omega_1}$, and $z_2 = e^{-j\omega_2}$.

Identifying a transfer function H(z1, z2) similar to (1) is required for the design of 2D filters so that the magnitude function $M(\omega_1, \omega_2) = H(e^{-j\omega_1}, e^{-j\omega_2})$ approximates the desired amplitude response Md ($\omega1$, $\omega2$) in some optimal sense. This approximation can be attained by reducing ϕ, where:

$$\phi = \phi\left(u_{ij}, v_{k,}, w_k, x_k, H_0\right) = \sum_{n_1=0}^{N_1} \sum_{n_2=0}^{N_2} [|M(\omega_1, \omega_2)| - M_d(\omega_1, \omega_2)]^{\rho}, \quad (2)$$

where $\omega_1 = \left(\pi/_{N_1}\right) n_1$, $\omega_2 = (\pi/_{N_2}) n_2$ and ρ is the positive integer. Therefore, minimizing the difference between the filter's real and desired amplitude response at the N1×N2 gird points is the major objective. The stabilization criteria are met because the denominator only has elements of the first degree:

$$|v_k + w_k| - 1 < x_k < 1 - |v_k - w_k|, for\ k = 1,2, \dots \dots N. \quad (3)$$

As a result, the restricted minimization issue described below can be used to describe the design challenge of 2D recursive filters: minimizing $\phi = \sum_{n_1=0}^{N_1} \sum_{n_2=0}^{N_2} [|M(\omega_1, \omega_2)| - M_d(\omega_1, \omega_2)]^{\rho}$ while adhering to the limitations indicated in (3).

The transfer function of the second-order 2D filter is displayed below, assuming N=2:

$$\begin{gathered} H(z_1, z_2) = H_0(u_{00} + u_{01} z_2 + u_{02} z_2^2 + u_{10} z_1 + u_{20} z_1^2 + u_{11} z_1 z_2 + \\ u_{12} z_1 z_2^2 + u_{21} z_1^2 z_2 + u_{22} z_1^2 z_2^2) \times ((1 + v_1 z_1 + w_1 z_2 + x_1 z_1 z_2) \times \\ (1 + v_2 z_1 + w_2 z_2 + x_2 z_1 z_2))^{-1}. \end{gathered} \quad (4)$$

Substitute $z_1 = e^{-j\omega_1}$, and $z_2 = e^{-j\omega_2}$ in (4), then $M(\omega_1, \omega_2)$ is given by:

$$\begin{gathered} M(\omega_1, \omega_2) = H_0[(u_{00} + u_{01} p_{01} + u_{02} p_{02} + u_{10} p_{10} + u_{20} p_{20} + \\ u_{11} p_{11} + u_{12} p_{12} + u_{21} p_{21} + u_{22} p_{22}) \times (X)^{-1} - j(u_{01} g_{01} + \\ u_{02} g_{02} + u_{10} g_{10} + u_{20} g_{20} + u_{11} g_{11} + u_{12} g_{12} + u_{21} g_{21} + \\ u_{22} g_{22}) \times (X)^{-1}], \end{gathered} \quad (5)$$

where:

$$\begin{gathered} X = [(1 + v_1 p_{10} + w_1 p_{01} + x_1 p_{11}) - j(v_1 g_{10} + w_1 g_{01} + x_1 g_{11})] \times \\ [(1 + v_2 p_{10} + w_2 p_{01} + x_2 p_{11}) - j(v_2 g_{10} + w_2 g_{01} + x_2 g_{11})], \\ p_{ab} = \cos(a\omega_1 + b\omega_2), \\ g_{ab} = \sin(a\omega_1 + b\omega_2) \text{ for a, b=0,1,2.} \end{gathered} \quad (6)$$

From (6), $M(\omega_1, \omega_2)$ can be written as:

$$M(\omega_1, \omega_2) = H_0\left(\frac{U_R - jU_I}{(V_{1R} - jV_{1I})(V_{2R} - jV_{2I})}\right), \tag{7}$$

where:

$$U_R = (u_{00} + u_{01}p_{01} + u_{02}p_{02} + u_{10}p_{10} + u_{20}p_{20} + u_{11}p_{11} + u_{12}p_{12} + u_{21}p_{21} + u_{22}p_{22}),\ U_I = (u_{01}g_{01} + u_{02}g_{02} + u_{10}g_{10} + u_{20}g_{20} + u_{11}g_{11} + u_{12}g_{12} + u_{21}g_{21} + u_{22}g_{22}),\ V_{1R} = (1 + v_1p_{10} + w_1p_{01} + x_1p_{11}), V_{1I} = (v_1g_{10} + w_1g_{01} + x_1g_{11}), V_{2R} = (1 + v_2p_{10} + w_2p_{01} + x_2p_{11}),\ V_{2I} = (v_2g_{10} + w_2g_{01} + x_2g_{11}). \tag{8}$$

The 2D IIR filter's magnitude response will be seen as follows:

$$|M(\omega_1, \omega_2)| = H_0\frac{\sqrt{u_R^2 + U_I^2}}{\sqrt{(V_{1R}^2 + V_{1I}^2)(V_{2R}^2 + V_{2I}^2)}}. \tag{9}$$

The 2D IIR filter is now designed to mitigate prior technologies' drawbacks. The optimization algorithm applied in the 2D IIR filter will be seen in the next phase.

4. Designing of 2d-IIR filter using a fused ESMA-Pelican Optimization Algorithm (FEPOA). Over the past few decades, metaheuristic algorithms (MA) have experienced tremendous progress and have found success in various domains. Many new MAs have been created to create IIR filters in recent years. Enhanced Slime Mould Algorithm (ESMA) is a metaheuristic procedure developed to overcome the shortcomings of the Slime Mould System for the application of IIR Filter design problems, but it still has some limitations. For the structure of the IIR filter, ESMA did not perform well compared to other algorithms. ESMA algorithm has a lower convergence speed and does not attain a better solution structure. Also, ESMA did not achieve a faster convergence rate and better convergence precision. ESMA's convergence accuracy is suboptimal and still has to be improved. Thus a new technique should be drawn to overcome the inadequacies.

We have suggested a new Fused ESMA-Pelican Optimization Algorithm to address these issues in the designed 2D IIR Filter. To increase the convergence speed, rate, and precision and get better performance, the Pelican Optimization Algorithm is combined with ESMA and made a hybrid algorithm. The first and foremost step in the optimization process is population initialization, done by the Chaotic approach. It creates a group of a good standard with good starting population diversity, a high convergence rate, etc. After initialization, now the position of population members should be identified and corrected since there is a chance that some individuals can be beyond the boundary search region. By simulating the pelican's tactical approach, the scanning of the search space and the exploration power of the FEPOA may be improved. This approach identifies the population member's location and then moves towards the identified area to correct them to the boundary search region. Then the Fitness is calculated and identified at random. This procedure increases the local search and exploitation power. The program then repeats the following repetition, updating the top candidate answer (every population element represents a contender option) and repeating the different FEPOA stages until the entire execution is finished. The program repetitions' top candidate solution is offered as the best possible answer. From this, the convergence rate is enhanced. Overall the speed of convergence, convergence precision and convergence accuracy in the final solution is increased, and the performance of the proposed FEPOA is improved. The IIR Filter design is now using the proposed FEPOA technique.

The following Figure 1 shows the block diagram of the proposed work, designing a 2D-IIR Filter Using a Fused ESMA-Pelican Optimization Algorithm (FEPOA).

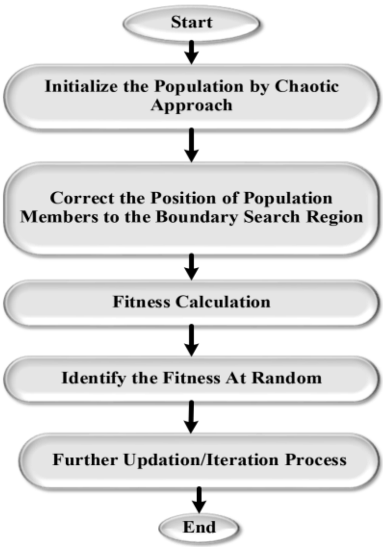

Fig. 1. Block Diagram of Designing 2D-IIR Filter Using a Fused ESMA-Pelican Optimization Algorithm (FEPOA)

4.1. Chaotic approach for Population Initialization. Ergodicity, pseudo-randomness, and sensitivity to beginning conditions are features of chaos. Chaos theory has thus been applied in numerous domains during the last few decades, including parameter optimization, feature selection, and chaotic control. The use of chaotic mapping to improve metaheuristic algorithms such as chaotic factor management, chaotic initiation, and chaotic local search has grown significantly in recent years. This study creates a chaotic sequence using the logistic chaos map. The logistic map has the following formulation and is one of the most straightforward and popular chaotic sequences:

$$a_{j+1} = \varphi . a_j(1 - a_j), \tag{10}$$

where φ is the control parameter when $\varphi = 4$, the logic series emerges chaotic a_j indicates the chaotic sequence value of the jth slime mould, $a_0 \in (0, 1)$, and a_0 is utilized to constitute a primary populace of slime mould.

The diversity of the inhabitants can be improved; convergence can happen faster, there is a lower danger of entering a tiny local number, and the quality of the solution is higher. The initial population for most metaheuristic algorithms is dispersed uniformly and randomly. This method might result in the methods entering a local minimum because of its slow convergence rate and low population characteristics. And previous research has shown that the community chaos initiation technique is superior to the initial solution. To boost the initial population variety, the first population in this section is formed using a logical chaotic value, and the chaotic disturbance is then added to it. The following equation describes below:

$$A^*_{j,k} = \mu_{j,k} . A_{j,k}, \tag{11}$$

where $\mu_{j,k}$ is the kth rate of the logistic series of the jth slime mould and $A^*_{j,k}$ is the jth slime mould's situation with chaotic disturbance.

Equation (12) generates the population members statistically based on the situation's bottom and higher bound:

$$a_{j,k} = b_k + rand \cdot (h_k - b_k)\ j = 1,2, \dots \dots M\ , k = 1,2, \dots \dots n, \tag{12}$$

where M is the number of members of a population, n is the number of issue variables, and the rand is a random variable in the range [0, 1], and $a_{j,k}$ is the value of the kth variable indicated by the jth candidate solution,

b_k is the kth bottom bound, and h_k is the kth higher bound of problem variables.

4.2. Pelican tactical approach. A matrix known as the population matrix in equation (13) is used to identify the pelican population members in the FEPOA. In this matrix, each row denotes a candidate solution, and each column denotes a suggested value for each parameter in a dilemma:

$$A = \begin{bmatrix} A_1 \\ \vdots \\ A_j \\ \vdots \\ A_M \end{bmatrix}_{M\times n} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,k} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{j,1} & \cdots & a_{j,k} & \cdots & a_{j,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{M,1} & \cdots & a_{M,k} & \cdots & a_{M,n} \end{bmatrix}_{M\times n}, \tag{13}$$

where A is the pelican population matrices and A_j is the jth pelican.

Every member of the population in the envisaged FEPOA is a pelican, a candidate fix for the issue. As a result, the optimal solution of the given scenario can be evaluated depending on the potential options. Equation (14) describes the use of a vector known as the objective function vector to forecast the parameters acquired for the objective function:

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_j \\ \vdots \\ G_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} G(A_1) \\ \vdots \\ G(A_j) \\ \vdots \\ G(A_M) \end{bmatrix}_{M\times 1}, \tag{14}$$

where Gj is the objective value of the function of the jth feasible solution, and G is the objective function vector. To improve candidate solutions, the suggested FEPOA resemble the actions and tactics used by pelicans during attacks and hunt determination. There are two steps to this pelican's tactical approach:

4.2.1. Search stage. During the initial stage, the pelicans locate the member's location and then hover toward it. Modelling this pelican's tactical approach allows for scanning of the search area and enables the proposed FEPOA to investigate new areas of the search area. The member's placement in the search space is produced randomly, which is a key aspect of FEPOA. It strengthens FEPOA's ability to conduct a precise search in the problem-solving domain. The ideas above and the pelican's approach to the member's location are statistically predicted in equation (15):

$$a_{j,k}^{S1} = \begin{cases} a_{j,k} + rand \cdot \left(m_j - I \cdot a_{j,k}\right),\ G_s < G_j \\ a_{j,k} + rand \cdot \left(a_{j,k} - m_j\right),\ else \end{cases}, \tag{15}$$

where $a_{j,k}^{S1}$ depends on stage 1, the new position of the jth pelican in the kth level. I is a chance quantity that can either be one or two. m_j is the location of the member in the kth dimension, and G_s is its objective function value. The element I is a quantity that, at random, might be either 1 or 2. For each iteration and member, this parameter is chosen at random. When this parameter's value equals two, a member experiences more movement, which may take them to fresher regions of the search space. As a result, parameter *I* influences the FEPOA's ability to precisely examine the search area. If the value of the objective function at that site is enhanced, the new role for a pelican in the proposed FEPOA is accepted. The mechanism is stopped from moving to less-than-ideal locations in this type of updating, sometimes referred to as effective updating. Equation (16) provides a representation of this process:

$$A_j = \begin{cases} A_j^{S1},\ G_j^{S1} < G_j \\ A_j,\quad else \end{cases}, \tag{16}$$

where A_j^{S1} is the new status of the jth pelican and G_j^{S1} is its objective function value based on stage 1.

4.2.2. Manipulation stage. The pelicans distribute their location around the area in the second phase after they arrive to move the members upward before gathering them in their search area. Pelicans captured more people in the attacked region due to this tactic. The proposed FEPOA converges to select regional locations due to replicating this pelicans' behavior. This procedure improves FEPOA's capability for local search and exploitation. For the algorithm to converge to a better solution, it is necessary to investigate the locations near the pelican site mathematically. Equation (17) describes this pelican behavior as it is engaged in searching given below:

$$a_{j,k}^{S2} = a_{j,k} + X \cdot \left(1 - \frac{i}{I}\right) \cdot (2.rand - 1) \cdot a_{j,k}, \tag{17}$$

where $a_{j,k}^{S2}$ is the innovative position of the jth pelican in the kth dimension based on Stage 2, X is a constant, which is equal to 0.2, $X \cdot \left(1 - \frac{i}{I}\right)$ is the neighborhood radius of $a_{j,k}$. While i is the iteration counter, I is the maximum quantity of iterations. The radius of the population members' local search areas to find a more effective solution is represented by the coefficient $X \cdot \left(1 - \frac{i}{I}\right)$. This coefficient can be used to increase the FEPOA's exploitation power and get the problem nearer to the optimal global solution. A bigger region around each member is taken into account in the beginning iterations since the value of this coefficient is high. The radius of each member's neighborhood gets smaller as the method replicates higher because the $X \cdot \left(1 - \frac{i}{I}\right)$ coefficient diminishes. It allows us to survey the space about every person in the group with fewer but more accurate stages, allowing the FEPOA to converge to answers that are nearer to the worldwide (or even precisely worldwide) ideal depending on the usage paradigm. At this stage, the new pelican location has also been accepted or rejected through effective upgrading, which is given as equation (18):

$$A_j = \begin{cases} A_j^{S2}, & G_j^{S2} < G_j \\ A_j, & else \end{cases}, \tag{18}$$

where A_j^{S2} is the jth pelican's innovative position, then G_j^{S2} is depending on stage 2's objective function value. When several population members were already improved depending on the initial and second levels, the best candidate solution up to that point will be upgraded following the new population status as well as the variables of the goal component. The algorithm moves on to the following iteration, repeating the various phases of the suggested FEPOA based on Equations (15) – (18) until the full execution is complete. As a quasi-optimal response to the stated issue, the best candidate solution discovered through algorithm iterations is shown at the end. The suggested FEPOA's computational complexity depends on four concepts: algorithm initialization, fitness function calculation, generation of a member, and solution upgrading. The initialization of the algorithms has a computational complexity $O(M)$. Each population element evaluates the optimal solution in both phases in every iteration. Therefore, the evaluation of the fitness function has a $O(2 \cdot I \cdot M)$ computational complexity. The computational complexity of generating members is $O(I) + O(I \cdot n)$, where the member is formed and evaluated at every repetition. The quantity of M population members with n dimensions during each cycle should be changed twice. Therefore, the computational difficulty of updating solutions is $O(2 \cdot I \cdot M \cdot n)$. As a result, the suggested FEPOA's overall computational complexity is equivalent to $O(M + I \cdot (1 + n) \cdot (1 + 2 \cdot M))$. The Figure 2 represents the Flow chart for the Fused ESMA-Pelican Optimization Algorithm (FEPOA) is given below.

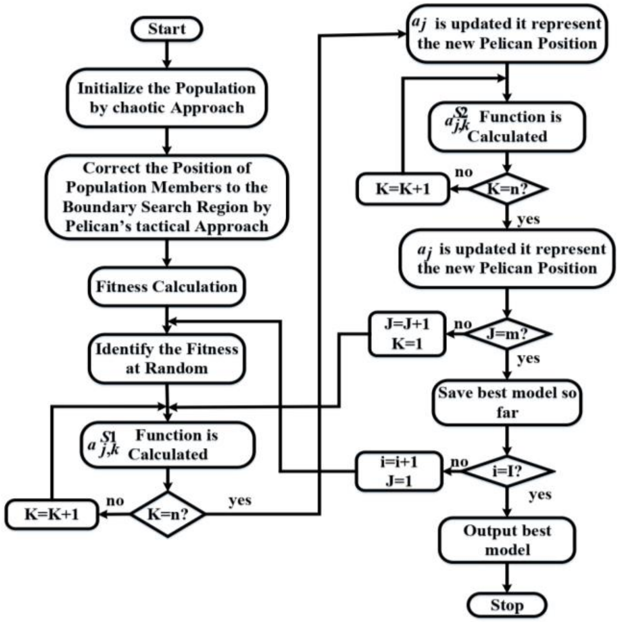

Fig. 2. Flow chart for the Fused ESMA-Pelican Optimization Algorithm (FEPOA)

Algorithm 1. Fused ESMA-Pelican Optimization Algorithm (FEPOA)

Step 1:	Start FEPOA
Step 2:	Input : optimization issue data
Step 3:	Initialize the position of the population members and correct the position
Step 4:	Calculate the fitness function and identify randomly
Step 5:	For i=1:I
Step 6:	Originate the position of members at random
Step 7:	For J=1:M
Step 8:	Stage 1:Search Stage (migrate towards the members)
Step 9:	For K=1:n
Step 10:	Evaluate recent condition of the kth dimension using Eq.(13)
Step 11:	End
Step 12:	Upgrade the jth population member using Eq.(14)
Step 13:	Stage 2:Manipulation Stage
Step 14:	For K=1:n
Step 15:	Evaluate recent condition of the kth dimension using Eq.(15)
Step 16:	End
Step 17:	Upgrade the jth population member using Eq.(16)
Step 18:	End
Step 19:	Upgrade best candidate Solution
Step 20:	End
Step 21:	Output: Best candidate solution attained by FEPOA
Step 22:	End FEPOA

As a result, the proposed FEPOA algorithm is applied to the IIR filter design. In that algorithm, the speed of convergence, convergence precision and convergence accuracy in the final solution is increased, and the performance is also increased in the overall filter design.

5. Simulation results and discussion. This part provides examples of the proposed technique's implementation outcomes with comparative findings. The Proposed method is simulated via MATLAB R2021a on Intel(R)core(TM)i5 10400 CPU@2.66 GHz, 4 GB RAM.

Figure 3 depicts the plot between the normalized Frequency Vs Magnitude. The graph reveals that if the normalized Frequency is zero, the magnitude will be high as well as if the normalized Frequency is increased, then the magnitude tends to decrease gradually. Also, it attains zero in magnitude when the normalized Frequency attains high.

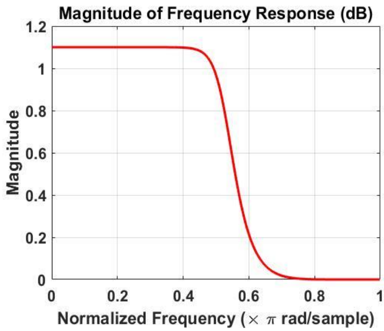

Fig. 3. Magnitude of Frequency Response in IIR Filter

Figure 4 reveals the passband group delay in the IIR filter design. In that graph, the group delay in the passband is between 0.4π rad/sample to 0.7 π rad/sample.

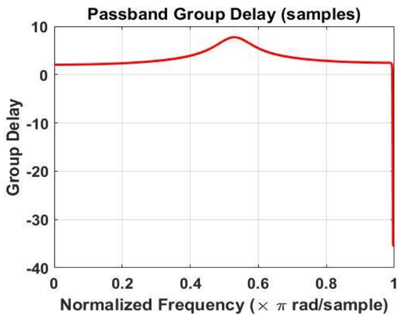

Fig. 4. Passband Group delay

Figure 5 reveals that the magnitude output will also increase when the normalized frequency increases. As in the pass band region, the normalized Frequency between 0.38 π rad/sample to 0.42 π rad/sample, the frequency response magnitude will attain a maximum of 55dB.

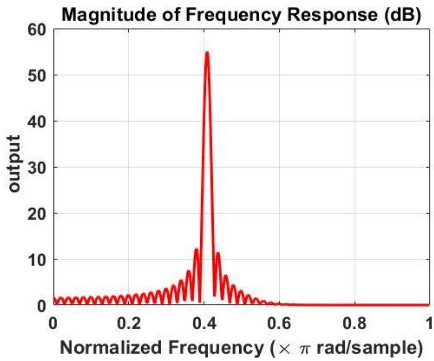

Fig. 5. Magnitude of Frequency Response with output

Figure 6 represents the fitness calculation of the Proposed FEPOA, considering the 200 iterations. In the initial stage, the Fitness will be high, which diminishes the convergence. If the iteration increases, the Fitness of the FEPOA will not enhance the convergence nor give the best candidate solution.

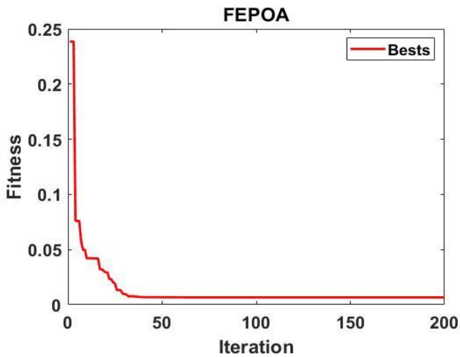

Fig. 6. Fitness calculation

Figure 7 reveals that the amplitude response that yields the proposed FEPOA has the best solution in the IIR filter design with a pass band that will attain 0.82 with $\rho = 2$.

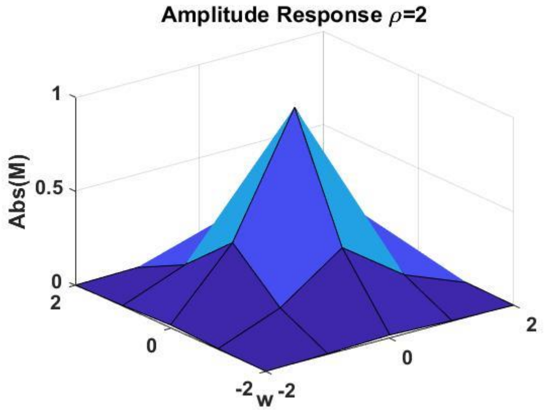

Fig. 7. Amplitude Response for the 2D IIR filter design with $\rho = 2$

Figure 8 reveals that the amplitude response that yields the proposed FEPOA has the best solution in the IIR filter design with a pass band that will attain 0.9 with $\rho = 4$.

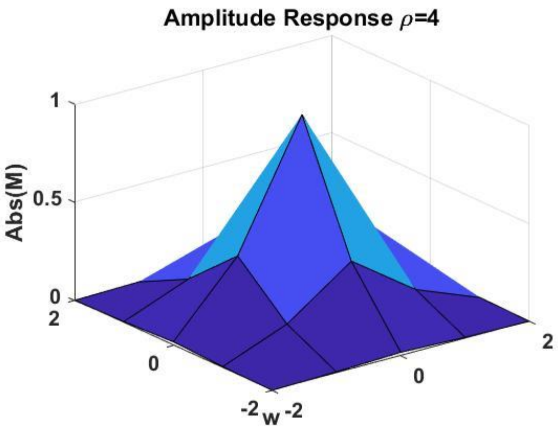

Fig. 8. Amplitude Response for the 2D IIR filter design with $\rho = 4$

Figure 9 reveals that the amplitude response that yields the proposed FEPOA has the best solution in the IIR filter design with a pass band that will attain 0.98 with $\rho = 8$.

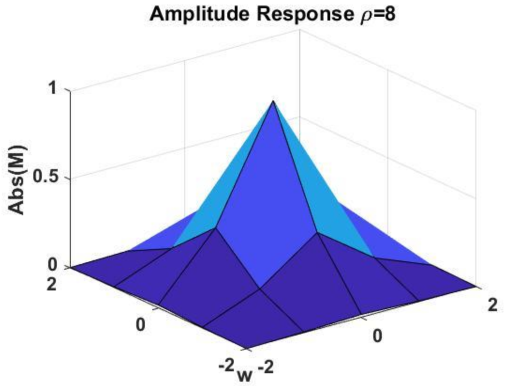

Fig. 9. Amplitude Response for the 2D IIR filter design with $\rho = 8$

Table 1 describes the coefficients values compared with prior algorithms such as Genetic Algorithm (GA), Particle swarm Optimization (PSO), Simulated Annealing based Particle Swarm Optimization (SAPSO) with FEPOA gives the best results for 2D IIR filter.

Table 1. Best Results for 2D IIR filter coefficients for various approaches with $\rho = 2$

Coefficients	GA [25]	PSO [26]	SAPSO [27]	FEPOA
u01	1.8162	1.8569	0.3069	0.2680
u02	-1.1060	1.5657	-0.9806	1.2145
u10	0.0712	-1.638	0.1681	-0.2460
u11	-2.5132	0.7365	-0.0431	0.0843
u12	0.4279	1.4300	-0.1820	-0.1653
u20	0.5926	0.6666	-0.7270	0.5127
u21	-1.3690	1.4897	-0.3249	0.2456
u22	2.4326	0.1710	1.6358	1.5628
v1	-0.8662	-0.6196	-1.4201	-1.2364
v2	-0.8907	-0.9312	-0.9178	-0.8952
w1	-0.8531	-0.6380	-0.6530	-0.6290
w2	-0.8388	-0.9328	-0.9127	-0.8910
x1	0.7346	0.3233	1.0081	0.9578
x2	0.8025	0.8829	0.8545	0.8321
H0	0.0009	0.0002	0.0022	0.0019
ϕ	6.0276	3.0475	2.629	2.1153

Tables 2 and 3 depict the comparison of prior algorithms such as Genetic Algorithm (GA), Particle swarm Optimization (PSO), Simulated Annealing based Particle Swarm Optimization (SAPSO), Cuckoo Search Algorithm (CSA) and Improved Global Best Guided Cuckoo Search Algorithm (CSA) with proposed FEPOA in terms of the best and worst case as well as mean, variance and time. The computation time attained less when compared with the prior technique with the proposed FEPOA.

Table 2. Comparison table for various approaches in terms of the best and worst case with different ρ values

Algorithm	$\rho = 2$		$\rho = 4$		$\rho = 8$	
	Best	Worst	Best	Worst	Best	Worst
GA	3.1574	7.4938	0.2596	0.8510	0.0025	0.0145
PSO	2.7527	5.3467	0.1359	0.4566	6.34×10-04	7.2×10-03
SAPSO	2.629	5.6744	0.1309	0.3663	6.82×10-04	0.0044
CSA [28]	2.4831	4.6001	0.1672	0.3762	0.0031	0.0179
IGCSA [29]	2.4495	2.5869	0.1278	0.3481	5.42×10-04	3.97×10-03
Proposed FEPOA	2.1153	1.7893	0.1186	0.2784	4.23×10-04	2.18×10-03

Table 3. Comparison table for various approaches in terms of Mean, Variance and Average time

Algorithm	$\rho = 2$		$\rho = 4$		$\rho = 8$		**Average time (s)**
	Mean	VAR	Mean	VAR	Mean	VAR	
GA	4.6137	0.6160	0.4300	0.0688	0.0066	7.08×10-06	69.71
PSO	3.24	0.45611	0.236	0.00765	2.28×10-03	2.25×10-06	46.26
SAPSO	2.629	0.6296	0.230	0.00521	0.0027	1.25×10-06	30.07
CSA	3.08	0.382	0.2831	0.00378	0.00508	9.005×10-06	16.67
IGCSA	2.46	7.45×10-04	0.1766	3.92×10-03	0.00129	1.39×10-06	9.43
Proposed FEPOA	2.15	6.25×10-04	0.0956	2.18×10-03	0.000845	1.025×10-06	3.0518

6. Conclusion. In this paper, a fused ESMA-pelican Optimization Algorithm (FEPOA) is proposed to attain the convergence speed and precision and create the IIR Filter. In the Proposed FEPOA, initially, the 2D IIR filter is created, and FEPOA is applied in the IIR filter. At first, the population initialization is done by the Chaotic approach which gives the population diversity, and position of the population is identified and corrected by the individual in the boundary search region. Then the pelican Optimization Algorithm is examined for the search space and exploration power, after that randomly calculated the fitness value. The best solution is updated before moving on to iterations, and the FEPOA phases are repeated until the execution is completed. The best solution gives the optimal solution for the proposed FEPOA, which enhanced the performances such as speed of convergence, convergence precision and convergence accuracy. The results obtained through FEPOA achieved desired fitness and best solution for 200 iterations, and the amplitude response attained the maximum value for $\rho = 2,4,8$ as well as the execution time achieved with 3.0158s, which is significantly faster than the other Genetic Algorithms generally used for 2D IIR filters. Thus, the overall 2D IIR Filter design performance was enhanced.

References

1. Mohammadi A., Zahiri S.H., Razavi S.M., Suganthan P.N. Design and modeling of adaptive IIR filtering systems using a weighted sum-variable length particle swarm optimization. Applied Soft Computing. 2021. vol. 109. pp. 107529.
2. Stavrou V.N., Tsoulos I.G., Mastorakis N.E. Transformations for FIR and IIR filters' design. Symmetry. 2021. vol. 13. no. 4. pp. 533.
3. Agrawal N., Kumar A., Bajaj V., Singh G.K. Design of digital IIR filter: A research survey. Applied Acoustics. 2021. vol. 172. pp. 107669.
4. Lai X., Meng H., Cao J., Lin Z. A sequential partial optimization algorithm for minimax design of separable-denominator 2-D IIR filters. IEEE Transactions on Signal Processing. 2016. vol. 65. no. 4. pp. 876–887.
5. Shafaati M., Mojallali H. IIR filter optimization using improved chaotic harmony search algorithm. Automatika: Journal for Control, Measurement, Electronics, Computing and Communications. 2018. vol. 59. no. 3–4. pp. 331–339. DOI: 10.1080/00051144.2018.1541643.
6. Mittal T. A hybrid moth flame optimization and variable neighbourhood search technique for optimal design of IIR filters. Neural Computing and Applications. 2022. vol. 34. no. 1. pp. 689–704.
7. Pankaj L., Soni V. Design of Auto Adaptive IIR Filter Using Pth Optimization Algorithm and Artificial Neural Network Technique. i-Manager's Journal on Digital Signal Processing. 2021. vol. 9. no. 1. pp. 1.
8. Karthik V., Susmitha K., Saha S.K., Kar R. Invasive weed optimization-based optimally designed high-pass IIR filter and Its FPGA implementation. In Evolutionary Computing and Mobile Sustainable Networks. 2021. pp. 239–247.
9. Stubberud P. Digital IIR Filter Design Using a Differential Evolution Algorithm with Polar Coordinates. In 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC). 2022. pp. 1029–1035.
10. Alsahlanee A.T. Digital Filter Performance Based on Squared Error. In 2021 International Conference on Advanced Computer Applications (ACA). 2021. pp. 74–79.

11. Omar A., Shpak D., Agathoklis P. Improved Design Method for Nearly Linear-Phase IIR Filters Using Constrained Optimization. Journal of Circuits, Systems and Computers. 2021. vol. 30. no. 11. pp. 2150207.
12. Susmitha K., Karthik V., Saha S.K., Kar R. Biogeography-Based Optimization Technique for Optimal Design of IIR Low-Pass Filter and Its FPGA Implementation. In Evolutionary Computing and Mobile Sustainable Networks. 2021. pp. 229–237.
13. Kaur H., Saini S., Sehgal A. Optimal Designing of FIR Filter with Hybrid Bat Optimization Algorithm. In Innovations in Electronics and Communication Engineering. 2022. pp. 523–541.
14. Durmuş B. Infinite impulse response system identification using average differential evolution algorithm with local search. Neural Computing and Applications. 2022. vol. 34. no. 1. pp. 375–390.
15. Liang X., Wu D., Liu Y., He M., Sun L. An Enhanced Slime Mould Algorithm and Its Application for Digital IIR Filter Design. Discrete Dynamics in Nature and Society. 2021. vol. 2021. pp. 1–23. DOI: 10.1155/2021/5333278.
16. Datta D., Dutta H.S. High performance IIR filter implementation on FPGA. Journal of Electrical Systems and Information Technology. 2021. vol. 8. no. 2. DOI: 10.1186/s43067-020-00025-4.
17. Wang Y., Ding F., Xu L. Some new results of designing an IIR filter with colored noise for signal processing. Digital Signal Processing. 2018. vol. 72. pp. 44–58.
18. Singh S., Ashok A., Kumar M., Rawat T.K. Optimal design of IIR filter using dragonfly algorithm. In Applications of Artificial Intelligence Techniques in Engineering. 2019. pp. 211–223.
19. Loubna K., Bachir B., Izeddine Z. Optimal digital IIR filter design using ant colony optimization. In 2018 4th International Conference on Optimization and Applications (ICOA). 2018. pp. 1–5. DOI: 10.1109/ICOA.2018.8370500.
20. Liu A., Li P., Deng X., Ren L. A sigmoid attractiveness based improved firefly algorithm and its applications in IIR filter design. Connection Science. 2021. vol. 33. no. 1. pp. 1–25. DOI: 10.1080/09540091.2020.1742660.
21. Bui N.T., Nguyen T.M.T., Park S., Choi J., Vo T.M.T., Kang Y.H., Oh J. Design of a nearly linear-phase IIR filter and JPEG compression ECG signal in real-time system. Biomedical Signal Processing and Control. 2021. vol. 67. pp. 102431.
22. Ko H.J., Tsai J.J. Robust and computationally efficient digital IIR filter synthesis and stability analysis under finite precision implementations. IEEE Transactions on Signal Processing. 2020. vol. 68. pp. 807–1822.
23. Pepe G., Gabrielli L., Squartini S., Cattani L., Tripodi C. Gravitational search algorithm for IIR filter-based audio equalization. In 2020 28th European Signal Processing Conference (EUSIPCO). 2021. pp. 496–500.
24. Agrawal N., Kumar A., Bajaj V. A new method for designing of stable digital IIR filter using hybrid method. Circuits, Systems, and Signal Processing. 2019. vol. 38. no. 5. pp. 2187–2226.
25. Elkarami B., Ahmadi M. An efficient design of 2-D FIR digital filters by using singular value decomposition and genetic algorithm with canonical signed digit (CSD) coefficients. In 2011 IEEE 54th International Midwest Symposium on Circuits and Systems (MWSCAS). 2011. pp. 1–4. DOI: 10.1109/MWSCAS.2011.6026659.
26. Chaker H., Kameche S. Hybrid Approach to Design of Two Dimensional Stable IIR Digital Filter. Algerian Journal of Signals and Systems. 2020. vol. 5. no. 3. pp. 148–152.
27. Kaddouri L., Adamou-Mitiche A.B., Mitiche L. Design of Two-Dimensional Recursive Digital Filter Using Multi Particle Swarm Optimization Algorithm. Journal Européen des Systèmes Automatisés. 2020. vol. 53. no. 4. pp. 559–566.

28. Kumar M., Rawat T.K. Optimal fractional delay-IIR filter design using cuckoo search algorithm. ISA transactions. 2015. vol. 59. pp. 39–54.
29. Dhabal S., Venkateswaran P. An improved global-best-guided cuckoo search algorithm for multiplierless design of two-dimensional IIR filters. Circuits, Systems, and Signal Processing. 2019. vol. 38. no. 2. pp. 805–826.

Sharma Rakesh Kumar — employee, Department of electronics and communication engineering, Malaviya National Institute of Technology Jaipur. Research interests: finite element analysis. 2018rec9034@mnit.ac.in; Malviya Nagar, Jawahar Lal Nehru Marg, Jhalana Gram, 302017, Jaipur, India; office phone: +91(141)252-9087.

Sharma Krishan Kumar — Professor, Department of electronics and communication engineering, Malaviya National Institute of Technology Jaipur. Research interests: signal and image processing, fractional transforms, electromagnetics, wireless communications. The number of publications — 111. kksharma.ece@mnit.ac.in; Malviya Nagar, Jawahar Lal Nehru Marg, Jhalana Gram, 302017, Jaipur, India; office phone: +91(141)252-9087.

Varma Tarun — Associate professor, Department of electronics and communication engineering, Malaviya National Institute of Technology Jaipur. Research interests: signal processing, computer networks, nano-electronic devices, MNEMS. The number of publications — 26. tarun@mnit.ac.in; Malviya Nagar, Jawahar Lal Nehru Marg, Jhalana Gram, 302017, Jaipur, India; office phone: +91(141)252-9087.

УДК 004.7 **DOI** 10.15622/ia.22.3.7

Р. Шарма, К. Шарма, Т. Варма

ПРОЕКТИРОВАНИЕ 2D-БИХ-ФИЛЬТРА С ИСПОЛЬЗОВАНИЕМ АЛГОРИТМА ОПТИМИЗАЦИИ FUSED ESMA-PELICAN OPTIMIZATION ALGORITHM (FEPOA)

Шарма Р., Шарма К., Варма Т. **Проектирование 2D-БИХ-фильтра с использованием алгоритма оптимизации Fused ESMA-Pelican Optimization Algorithm (FEPOA).**

Аннотация. Многие приложения цифровой обработки сигналов (DSP) и электронные гаджеты сегодня требуют цифровой фильтрации. Для получения быстрых и улучшенных результатов использовались различные алгоритмы оптимизации. Некоторые исследователи использовали Enhanced Slime Mold Algorithm для разработки 2D БИХ-фильтра. Однако было замечено, что данный алгоритм не обеспечил лучшей структуры решения и имел более низкую скорость сходимости. Чтобы решить эту проблему, для разработки 2D БИХ-фильтра используется алгоритм оптимизации Fused ESMA-Pelican Optimization Algorithm (FEPOA), который объединяет Pelican Optimization Algorithm с Enhanced Slime Mould Algorithm (ESMA). Сначала для инициализации популяции используется хаотический подход, который обеспечивает высококачественную популяцию с превосходным разнообразием, после чего позиция членов популяции заключается в идентификации и корректировке особи в граничной области поиска. После этого с помощью тактического подхода пеликана (Pelican Tactical Approach) изучается пространство поиска и исследовательской мощности FEPOA, потом случайным образом вычисляется пригодность, и обновляется лучшее решение, а затем оно перемещается к итерациям. Фазы FEPOA повторяются до тех пор, пока не завершится выполнение. Далее лучшее решение дает оптимальное решение, которое повышает скорость сходимости, точность сходимости и производительность FEPOA. Затем FEPOA реализуется в БИХ-фильтре для улучшения общей конструкции фильтра. Результаты, предоставленные FEPOA, достигают необходимой пригодности и наилучшего решения для 200 итераций, а амплитудная характеристика достигает максимального значения для = 2,4,8, а также время выполнения 3,0158 с, что намного быстрее, чем другие генетические алгоритмы, часто используемые для 2D БИХ-фильтров.

Ключевые слова: FEPOA, БИХ-фильтр, член популяции, КИХ-фильтр, хаотический подход, тактический подход Пеликана.

Литература

1. Mohammadi A., Zahiri S.H., Razavi S.M., Suganthan P.N. Design and modeling of adaptive IIR filtering systems using a weighted sum-variable length particle swarm optimization. Applied Soft Computing. 2021. vol. 109. pp. 107529.
2. Stavrou V.N., Tsoulos I.G., Mastorakis N.E. Transformations for FIR and IIR filters' design. Symmetry. 2021. vol. 13. no. 4. pp. 533.
3. Agrawal N., Kumar A., Bajaj V., Singh G.K. Design of digital IIR filter: A research survey. Applied Acoustics. 2021. vol. 172. pp. 107669.
4. Lai X., Meng H., Cao J., Lin Z. A sequential partial optimization algorithm for minimax design of separable-denominator 2-D IIR filters. IEEE Transactions on Signal Processing. 2016. vol. 65. no. 4. pp. 876–887.
5. Shafaati M., Mojallali H. IIR filter optimization using improved chaotic harmony search algorithm. Automatika: Journal for Control, Measurement, Electronics,

Computing and Communications. 2018. vol. 59. no. 3–4. pp. 331–339. DOI: 10.1080/00051144.2018.1541643.
6. Mittal T. A hybrid moth flame optimization and variable neighbourhood search technique for optimal design of IIR filters. Neural Computing and Applications. 2022. vol. 34. no. 1. pp. 689–704.
7. Pankaj L., Soni V. Design of Auto Adaptive IIR Filter Using Pth Optimization Algorithm and Artificial Neural Network Technique. i-Manager's Journal on Digital Signal Processing. 2021. vol. 9. no. 1. pp. 1.
8. Karthik V., Susmitha K., Saha S.K., Kar R. Invasive weed optimization-based optimally designed high-pass IIR filter and Its FPGA implementation. In Evolutionary Computing and Mobile Sustainable Networks. 2021. pp. 239–247.
9. Stubberud P. Digital IIR Filter Design Using a Differential Evolution Algorithm with Polar Coordinates. In 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC). 2022. pp. 1029–1035.
10. Alsahlanee A.T. Digital Filter Performance Based on Squared Error. In 2021 International Conference on Advanced Computer Applications (ACA). 2021. pp. 74–79.
11. Omar A., Shpak D., Agathoklis P. Improved Design Method for Nearly Linear-Phase IIR Filters Using Constrained Optimization. Journal of Circuits, Systems and Computers. 2021. vol. 30. no. 11. pp. 2150207.
12. Susmitha K., Karthik V., Saha S.K., Kar R. Biogeography-Based Optimization Technique for Optimal Design of IIR Low-Pass Filter and Its FPGA Implementation. In Evolutionary Computing and Mobile Sustainable Networks. 2021. pp. 229–237.
13. Kaur H., Saini S., Sehgal A. Optimal Designing of FIR Filter with Hybrid Bat Optimization Algorithm. In Innovations in Electronics and Communication Engineering. 2022. pp. 523–541.
14. Durmuş B. Infinite impulse response system identification using average differential evolution algorithm with local search. Neural Computing and Applications. 2022. vol. 34. no. 1. pp. 375–390.
15. Liang X., Wu D., Liu Y., He M., Sun L. An Enhanced Slime Mould Algorithm and Its Application for Digital IIR Filter Design. Discrete Dynamics in Nature and Society. 2021. vol. 2021. pp. 1–23. DOI: 10.1155/2021/5333278.
16. Datta D., Dutta H.S. High performance IIR filter implementation on FPGA. Journal of Electrical Systems and Information Technology. 2021. vol. 8. no. 2. DOI: 10.1186/s43067-020-00025-4.
17. Wang Y., Ding F., Xu L. Some new results of designing an IIR filter with colored noise for signal processing. Digital Signal Processing. 2018. vol. 72. pp. 44–58.
18. Singh S., Ashok A., Kumar M., Rawat T.K. Optimal design of IIR filter using dragonfly algorithm. In Applications of Artificial Intelligence Techniques in Engineering. 2019. pp. 211–223.
19. Loubna K., Bachir B., Izeddine Z. Optimal digital IIR filter design using ant colony optimization. In 2018 4th International Conference on Optimization and Applications (ICOA). 2018. pp. 1–5. DOI: 10.1109/ICOA.2018.8370500.
20. Liu A., Li P., Deng X., Ren L. A sigmoid attractiveness based improved firefly algorithm and its applications in IIR filter design. Connection Science. 2021. vol. 33. no. 1. pp. 1–25. DOI: 10.1080/09540091.2020.1742660.
21. Bui N.T., Nguyen T.M.T., Park S., Choi J., Vo T.M.T., Kang Y.H., Oh J. Design of a nearly linear-phase IIR filter and JPEG compression ECG signal in real-time system. Biomedical Signal Processing and Control. 2021. vol. 67. pp. 102431.
22. Ko H.J., Tsai J.J. Robust and computationally efficient digital IIR filter synthesis and stability analysis under finite precision implementations. IEEE Transactions on Signal Processing. 2020. vol. 68. pp. 807–1822.

23. Pepe G., Gabrielli L., Squartini S., Cattani L., Tripodi C. Gravitational search algorithm for IIR filter-based audio equalization. In 2020 28th European Signal Processing Conference (EUSIPCO). 2021. pp. 496–500.
24. Agrawal N., Kumar A., Bajaj V. A new method for designing of stable digital IIR filter using hybrid method. Circuits, Systems, and Signal Processing. 2019. vol. 38. no. 5. pp. 2187–2226.
25. Elkarami B., Ahmadi M. An efficient design of 2-D FIR digital filters by using singular value decomposition and genetic algorithm with canonical signed digit (CSD) coefficients. In 2011 IEEE 54th International Midwest Symposium on Circuits and Systems (MWSCAS). 2011. pp. 1–4. DOI: 10.1109/MWSCAS.2011.6026659.
26. Chaker H., Kameche S. Hybrid Approach to Design of Two Dimensional Stable IIR Digital Filter. Algerian Journal of Signals and Systems. 2020. vol. 5. no. 3. pp. 148–152.
27. Kaddouri L., Adamou-Mitiche A.B., Mitiche L. Design of Two-Dimensional Recursive Digital Filter Using Multi Particle Swarm Optimization Algorithm. Journal Européen des Systèmes Automatisés. 2020. vol. 53. no. 4. pp. 559–566.
28. Kumar M., Rawat T.K. Optimal fractional delay-IIR filter design using cuckoo search algorithm. ISA transactions. 2015. vol. 59. pp. 39–54.
29. Dhabal S., Venkateswaran P. An improved global-best-guided cuckoo search algorithm for multiplierless design of two-dimensional IIR filters. Circuits, Systems, and Signal Processing. 2019. vol. 38. no. 2. pp. 805–826.

Шарма Ракеш Кумар — сотрудник, кафедра электроники и связи, Национальный технологический институт Малавии в Джайпуре. Область научных интересов: анализ методом конечных элементов. 2018rec9034@mnit.ac.in; Малвья Нагар, Джавахар Лал Неру Марг, Джалана Грэм, 302017, Джайпур, Индия; р.т.: +91(141)252-9087.

Шарма Кришан Кумар — профессор, кафедра электроники и связи, Национальный технологический институт Малавии в Джайпуре. Область научных интересов: обработка сигналов и изображений, дробные преобразования, электромагнетизм, беспроводная связь. Число научных публикаций — 111. kksharma.ece@mnit.ac.in; Малвья Нагар, Джавахар Лал Неру Марг, Джалана Грэм, 302017, Джайпур, Индия; р.т.: +91(141)252-9087.

Варма Тарун — доцент, кафедра электроники и связи, Национальный технологический институт Малавии в Джайпуре. Область научных интересов: обработка сигналов, компьютерные сети, наноэлектронные устройства, MNEMS. Число научных публикаций — 26. tarun@mnit.ac.in; Малвья Нагар, Джавахар Лал Неру Марг, Джалана Грэм, 302017, Джайпур, Индия; р.т.: +91(141)252-9087.