IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

# Design of Low Pass Digital FIR Filter Using Nature Inspired Technique

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**Abstract:** The digital filters play an important role in the field of science and technology. Due to phase linearity and frequency stability, digital finite impulse response (FIR) filters are used in number of applications. The various methods for the design of digital filters like particle swarm optimization (PSO), genetic algorithm (GA), differential evolution (DE) etc. and the modified version of these. This paper presents the hybrid predator prey optimization (HPPO) technique for the design of digital low pass FIR filter. HPPO has the capability of both exploration and exploitation of search space locally as well globally. This algorithm is used with the aim to achieve desired filter specifications for designing an optimal filter. This paper also compares the simulation results with hybrid differential evolution (HDE) algorithm. The simulation results show that the proposed design method is better than other optimization techniques in terms of objective function and magnitude errors for the design of low pass digital FIR filters.

**Keywords:** Digital Finite Impulse Response filters (FIR), Prey Predator Optimization, Exploratory move, Hybrid Predator Prey Optimization (HPPO), Hybrid Differential Evolution (HDE).

## I. INTRODUCTION

A filter is a device that removes some unwanted components or features from a signal. Filters could be analog or digital. Digital filters are commonplace and an essential element used in wide variety of applications such as signal processing, aerospace, defence equipments, telecommunications, audio and video processing. The main function of digital filters is fetched out the useful signal from other unwanted signals and eliminates the noise [9]. Nowdays digital filters are replacing the role of analog filters because of its advantages over the analog filter like small physical size, high accuracy and reliability. Digital filters are highly flexible and portable and have minimum or negligible interference noise.

Digital filters are mainly classified into two categories: finite impulse response (FIR) filters and infinite impulse response (IIR) filters depending on the length of the impulse response. FIR filters are also called non- recursive filters since they do not use feedback.

The IIR filters possess non-linear phase response. The main advantages of FIR filters over IIR filters is that they have linear phase and stable and less computational because only those outputs are calculated which are going to be used which makes FIR filters as a powerful component in the most of the applications of science and technology [2,5]. There are many well known optimization methods for the design of digital filters [4] such as window method, genetic algorithm, differential evolution method etc.

## II. RELATED WORK

Goel et. al. (2015) has design a low pass FIR filter using window method like hamming, hanning, kaiser, blackman, tukey and rectangular window. The main principle is to design Low pass filter with sampling frequency 5000 Hz and Cut-off frequency 1000 Hz. Magnitude and phase responses of low pass filter using various window techniques are demonstrated [7]. The main advantage of window technique is that impulse response coefficients can be obtained easily instead of solving complex optimization problems. The major disadvantages are the poor control of critical frequencies such as stop band and pass band cut-off frequencies.

To overcome the problem of window method, Kaur et. al. (2012) has implemented genetic algorithm for optimization of FIR filters. GA offers a quick, simple and automatic method of designing low pass FIR filters that are very close to optimum in terms of magnitude response, frequency response and in terms of phase variation [1]. But the problem with GA is its convergence speed.

Neha et. al. (2014) has designed a linear phase FIR low pass filter using particle swarm optimization technique. PSO is algorithm results in an optimal coefficient set for linear phase FIR filter approximating the ideal specifications [5]. The merits of PSO are: simple implementation and convergence speed is controlled via some parameters. But it has some demerits also like premature convergence and stagnation problem. To overcome these limitations Rani et. al. (2015)

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

implemented craziness based PSO which is modification to PSO for the design of FIR filter [8].

These methods are not suitable for optimal filter design at higher orders. So, in this paper a hybrid predator prey optimization (HPPO) method has been presented for the design of digital FIR low pass filter. HPPO explores the search space globally as well as locally by varying control parameters such as population size, acceleration constants etc. to achieve minimum objective function, magnitude errors and pass band and stop band ripples. HPPO technique have been used that is the hybridization of Predator prey optimization technique, exploratory move technique and opposition based learning for FIR low pass filter design which tries to match the required specifications for an optimal filter design.

The rest of this paper has been arranged as follows. In section II, FIR filter design problem statement has been formulated. Section III discusses the PPO algorithm and algorithm of Exploratory Move. Section IV consists of simulation results obtained for low pass filter. Finally section V concludes the paper.

## III. PROBLEM FORMULATION

This section discusses the design of digital FIR filter. Finite impulse response filter is a filter of finite duration, because it settles to zero in finite time. If a single impulse is present at input of an FIR filter and all subsequent input's are zero, output of an FIR filter becomes zero too after a finite time. FIR filters are simplest to design and termed as a non-recursive type because it depends on present values only and no dependence on past values. The conventional design of FIR digital filter described by difference equation:

$$y(n) = \sum_{k=0}^{M-1} b_k\, x(n-k) \qquad (1)$$

Here y (n) is output sequence, x (n) is input sequence, $b_k$ is coefficient and M is the order of the filter. The transfer function of FIR filter is given as:

$$\mathrm{H(z)} = \sum_{k=0}^{M-1} b_k\, z^{-k} \qquad (2)$$

The unit sample response of FIR system is identical to the coefficients ($b_k$) is stated as:

$$h(n) = \begin{cases} b_n & 0 \le n \le M-1 \\ 0 & otherwise \end{cases} \qquad (3)$$

We can also express the output sequence as the convolution of unit sample response h (n) of the system with its input signal.

$$y(n) = \sum_{k=0}^{M-1} h(k)x(n-k) \qquad (4)$$

FIR filter is designed by searching for best filter order and filter coefficients that meet certain specifications. The performance of FIR filter is evaluated by using $L_1$ and $L_2$-norm approximation error of magnitude response and ripple magnitude of both pass-band and stop-band. The FIR filter is designed by optimizing the filter coefficients. The magnitude response is specified at K equally spaced discrete frequency points in pass band and stop band.

$$E(x) = \sum_{i=0}^{K} \{\left|H_d(wi) - |H(w_i, x)|\right|^p\}^{\frac{1}{p}} \qquad (5)$$

where $H_d(wi)$ is the desired magnitude response of the ideal FIR filter and $H(\omega_i, x)$ is the obtained magnitude response of the FIR filters.
For p=1, magnitude error denotes the $L_1$ norm error and p=2 magnitude error denotes the $L_2$-norm error.
$e_1(x)$ - absolute error $L_1$-norm for magnitude response
$e_2(x)$ - squared error $L_2$-norm of magnitude response
$e_1(x)$ and $e_2(x)$ are expressed as:

$$e_1(x) = \sum_{i=0}^{K} \left|H_d(wi) - |H(w_i, x)|\right| \qquad (6)$$

$$e_2(x) = \sum_{i=0}^{K} \left(\left|H_d(\omega i) - |H(\omega_i, x)|\right|\right)^2 \qquad (7)$$

Desired magnitude response of digital FIR filter is given as:

$$H_d(\omega_i) = f(x) = \begin{cases} 1, & for\ \omega_i\ \varepsilon\ \text{passband} \\ 0, & for\ \omega_i\ \varepsilon\ \text{stopband} \end{cases} \qquad (8)$$

$\delta_p$ and $\delta_s$ are the ripple magnitude of pass band and stop band which are to be minimized.

$$\delta_p(x) = max_{\omega i}|H(\omega_i, x)| - min_{\omega i}|H(\omega_i, x)| \quad \ldots \ldots for\ \omega_i \varepsilon\ passband \qquad (9)$$

$$\delta_s(x) = max_{\omega i}|H(\omega_i, x)| \quad \ldots \ldots for\ \omega_i \varepsilon\ stopband \qquad (10)$$

Multivariable optimization problem is stated as:

- $M_1$ (x) = Minimize $e_1$ (x)
- $M_2$ (x) = Minimize $e_2$ (x)
- $M_3$ (x) = Minimize $\delta_p$ (x)
- $M_4$ (x) = Minimize $\delta_s$ (x)

The multi- objective function is converted to single objective function:


DOI 10.17148/IJARCCE.2016.5831

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified

Vol. 5, Issue 8, August 2016

$$M(x) = \sum_{j=1}^{4} \omega_j \ M_j(x) \qquad (11)$$

$\omega_j$ is weighting function.

## III. OPTIMIZATION TECHNIQUES

### Hybrid Predator Prey Optimization

Hybrid predator prey optimization is the hybridization of predator prey optimization, exploratory move to fine tune the solution in promising search area and opposition based strategy to start with best solution. This section gives the brief discussion of predator prey optimization technique, exploratory search technique and their algorithms. This section also talks about opposition based strategy, initialization of population position and velocity and evaluation of position and velocity of predator and preys.

### Predator prey optimization

Predator prey optimization technique is a global search technique in which number of preys and a single predator has been participates. This technique is based on particle swarm optimization (PSO) with addition of predator effect. PSO is a population based technique based on movements of swarms. It has the capability to handle larger search space and particles are randomly selected for this search space [6]. Particles change its position according to their own flying experience and flying experience of neighbouring particles. The particles update its position by adding velocity vector to position vector.

In PPO model preys play the role of diversification in search of best point due to the fear of predator. The predator attracts the best particle in the group, while repelling other particles. Prey particles always try to attain best position in order to keep away from the attack of predator. The probability factor controls the effect of predator on any prey in the group. By controlling the frequency and strength of the meetings between predator and prey exploration and exploitation is maintained. In PPO, predator is used to search around global best space, whereas preys search for a solution space roughly escaping from predators, which helps to avoids premature convergence [3].

### Initialization of Population Position and Velocity

The Initial positions of preys and predator are chosen randomly between upper and lower limits. Total population consists of $N_p$ preys and a single predator.

Prey and predator positions, $x_{ik}^0$ and $x_{pi}^0$ , respectively of FIR filter coefficients (decision variables) are randomly initialized within their respective upper and lower limits.

$$x_{ik}^0 = x_i^{\min} + R_{ik}^1 (x_i^{\max} - x_i^{\max}) \qquad (12)$$

$$x_{Pi}^0 = x_i^{\min} + R_i^2 (x_i^{\max} - x_i^{\max}) \qquad (13)$$

where $x_i^{min}$ and $x_i^{max}$ are respresenting the upper and lower limit of $i^{th}$ decision variables. $R_{ik}^1$ and $R_i^2$ are uniform random numbers having value between 0 and 1.

Prey and predator velocities, $V_{ik}^0$ and $V_{pi}^0$ , respectively of decision variables which are randomly initialized within their respective predefined limits.

$$V_{ik}^0 = V_i^{\min} + R_{ik}^1 (V_i^{\max} - V_i^{\min}) \qquad (14)$$

$$V_{Pi}^0 = V_i^{\min} + R_{Pi}^1 (V_i^{\max} - V_i^{\min}) \qquad (15)$$

where minimum and maximum prey velocities are set using the relation:

$$V_i^{min} = -\alpha\left(x_i^{max} - x_i^{min}\right) \qquad (16)$$

$$V_i^{max} = +\alpha\left(x_i^{max} - x_i^{min}\right) \qquad (17)$$

By varying the value of $\alpha$, minimum and maximum velocities of preys are obtained. $\alpha$ is equals to 0.25.

### Predator Velocity and Position Evaluation

The predator velocity and position of decision variables, updates for $(t+1)^{th}$ iteration are given below:

$$V_{P_i}^{t+1} = C_4(\mathrm{GP}best_i^t \text{-} P_{Pi}^t) \quad \text{(i=1, 2,.,S)} \qquad (18)$$

$$x_{Pi}^{t+1} = x_{Pi}^t + V_{Pi}^{t+1} \quad \text{(i=1, 2,.......,S)} \qquad (19)$$

where, GP$best_i^t$ is best global prey position of $i^{th}$ variable; $C_4$ is random number ranging from 0 to upper limits; $x_{pi}$ is element of position of predator; $V_{pi}$ is velocity.

### Prey Velocity and Position Evaluation

The equation of velocity of prey particle for $(t+1)th$ iteration is given by:

$$V_{ik}^{t+1} = \begin{cases} wV_{ik}^t + AC_1R_1\left(xbest_{ik}^t - x_{ik}^t\right) + AC_2R_2\left(GPbest_{ik}^t - x_{ik}^t\right) & ;P_f \le P_f^{max} \\ wV_{ik}^t + AC_1R_1\left(xbest_{ik}^t - x_{ik}^t\right) + AC_2R_2\left(GPbest_{ik}^t - x_{ik}^t\right) + C_3\,a\left(e^{-b_e k}\right) & ;P_f > P_f^{max} \end{cases}$$

$$\text{(i=1,2,....,S; k=1,2,...,}N_p\text{)} \qquad (20)$$

The position of prey particle is given by the equation:

$$x_{ik}^{t+1} = x_{ik}^t + c_{cf} V_{ik}^{t+1} \quad \text{(i=1,2..,S;k=1,2,., } N_p\text{)} \qquad (21)$$

where, $C_1, C_2$ is acceleration constant; $R_{1,} R_2$ is random number having value in range [0,1]; w is weight of inertia; $xbest_i^t$ is local position of $t^{th}$ and $i^{th}$ population; a has maximum amplitude of predator effect on the prey and b is controlling factor; $C_3$ is random number in range of 0 and 1; $e_k$ is Euclidean distance between the position of prey and predator position for $k^{th}$ population.

Euclidean distance between the position of prey and predator position for $k^{th}$ population is given as:

$$e_k = \sqrt{\sum_{i=1}^{S}\left(x_{ik} - x_{pi}\right)^2} \quad (22)$$

$w$ is inertia weight which is computed as:

$$w = \left[w^{max} - \left(w^{max} - w^{min}\right)\left(\frac{t}{t_{max}}\right)\right] \quad (23)$$

$C_{fc}$ is a constriction factor given by following equation:

$$C_{fc} = \begin{cases} \left|2 - \emptyset - \sqrt{\emptyset^2 - 4\emptyset}\right| & if\ \emptyset \geq 4 \\ 1 & if\ \emptyset < 4 \end{cases} \quad (24)$$

The elements of prey positions $x_{ik}^t$, and velocities $V_{ik}^t$ may violate their limits. This violation is set by updating their values on violation either at upper and lower limits.

$$V_{ik}^t = \begin{cases} V_{ik}^t + R_3 V_i^{max} & ; if\ V_{ik}^t < V_i^{min} \\ V_{ik}^t + R_3 V_i^{max} & ; if\ V_{ik}^t > V_i^{max} \\ V_{ik}^t & ; no\ violation\ of\ limits \end{cases} \quad (25)$$

where $R_3$ any uniform random number between 0 and 1. The process is repeated till the limits are satisfied. In similar fashion predator velocity limits are adjusted.

**Opposition Based Strategy**

Optimization method starts with some initial solutions and these initial solutions are randomly chosen. These solutions have been improved with the aim to achieve best solution as per requirements. The process of searching for best solution terminates when some predefined criteria are satisfied. The process of searching starts with random guesses in the absence of any information about solution. The computational time is the distance between initial random solutions from the best solution. It can improve the chance of starting with a better solution by simultaneously analysing the opposite solution. By doing this, the better one either randomly chosen solution or opposite solution values can be chosen as an initial solution [11]. According to probability theory, 50% of the time, a guess is farther from the solution corresponding to its opposite guess. Therefore, starting with the closer of the two solutions as on the basis of its objective function has the potential to accelerate convergence. The similar approach is applied continuously to each solution in the current population.

$$x_{i+Np,j}^t = x_j^{min} + x_j^{max} - x_{ij}^t \quad (26)$$

$$(j = 1, 2, \ldots\ldots, S;\ \ i = 1, 2, \ldots\ldots, Np)$$

where $x_j^{min}$ and $x_j^{max}$ are lower and upper limits of filter coefficients.

**Exploratory Move**

Exploratory move is a local search technique. In the exploratory move, the current point is perturbed in both positive and negative directions with each variable one at a time and the best point is recorded. The current point is updated to the best point at the end of each design variable perturbation may either be directed or random. If the point found after the perturbation of all filter coefficients is different from original point, the exploratory move is a success; otherwise, the exploratory move is a failure. In any case, the best point is considered to be the outcome of the exploratory move. The starting point obtained with the help of random initialization is explored iteratively [3].

Filter coefficient x is initialized as follows:

$$x_i^n = x_i^o \pm \Delta_i u_i^j\,(i = 1,2, \ldots S; j = 1,2, \ldots S) \quad (27)$$

$$u_i^j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \quad (28)$$

The objective function denoted by $A(x_i^n)$ is calculated as follows:

$$x_i^n = \begin{cases} x_i^o + \Delta_i u_i^j & ; A\left(x_i^o + \Delta_i u_i^j\right) \leq A(x_i^o) \\ x_i^o - \Delta_i u_i^j & ; A\left(x_i^o - \Delta_i u_i^j\right) \leq A(x_i^o) \\ x_i^o & ; \mathrm{otherwise} \end{cases} \quad (29)$$

where $(i = 1,2, \ldots S)$ and $\Delta_i$ is random for global search and fixed for local search.

The process is repeated till all the filter coefficients are explored and overall minimum is selected as new starting point for next iteration. The stepwise algorithm to explore filter coefficients is given below.

**Algorithm 1: Exploratory Move**

1. Select small change, $\Delta_i$, and $x_i^o$ and then compute f $(x_i^o)$
2. Initialize iteration counter, IT=0
3. Increment the counter, IT=IT+1
4. IF IP >$IP^{max}$ GO TO 14
5. Initialize filter coefficient counter j=0
6. Increment filter coefficient counter, j=j+1
7. Find $u_i^j$ using equation 28
8. Evaluate Performance Function, $A\left(x_i^o + \Delta_i u_i^j\right)$ and $A\left(x_i^o - \Delta_i u_i^j\right)$
9. Select $x_i^n$ using equation 29 and $A(x_i^n)$
10. IF $(j \leq s)$, GO TO 6 and repeat.
11. IF $A(x_i^n) < A(x_i^o)$
12. THEN GO TO 5
13. ELSE $\Delta_i = \Delta_i/1.618$ and GOTO 3 and repeat.
14. STOP.

**Algorithm 2: Hybrid Predator Prey Optimization**

1. Initialize data like swarm size ($N_p$), minimum and maximum limits of velocity and position of prey and

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

predator, coefficients ($c_1$,$c_2$) maximum value of probability fear (pf), etc.
2. Randomly initialize the positions of the prey and predator which are the decision variables.
3. Randomly initialize the velocities of prey and predator.
4. Apply opposition based strategy.
5. Calculate objective function.
6. Select $N_p$ preys from total number of preys (2 $N_p$).
7. Assign all the prey positions as their local best position.
8. Calculate the global best position from the local best position of the prey.
9. Update predator position and velocity.
10. Randomly create the probability fear in the range between 0 and 1.
11. IF (probability fear > maximum probability fear )

THEN

Update the velocity and position with predator affect

ELSE

Update prey velocity and position without predator effect

END-IF.

12. Calculate augmented objective function for all prey population.
13. Update local best position and global best position of prey particles.
14. Perform exploratory move for modification of global best position of prey particles.
15. It stopping criteria is not met, repeat step 9.
16. Halt

## IV. SIMULATION RESULTS AND DISCUSSION

The proposed algorithm is simulated using MATLAB for the design of low pass digital finite impulse response filter for order (n) taken to be 20. The actual filter designed used all the parameters of ideal filter defined here as: - Initially order of filter is taken as 20 which results in number of coefficients 21. The algorithm is run 100 times and 200 iterations have been taken for obtaining best results at different orders. The designing of low pass filter is done by setting 200 equally spaced samples within frequency range [0, π].

The prescribed design conditions for the low pass FIR digital filter are shown in Table 1.

Table 1: Design conditions for band-pass FIR filter

| Filter Type | Pass Band | Stop Band | Max. value of \|H(w,x)\| |
|---|---|---|---|
| Low Pass | $0 \leq \omega \leq 0.2\pi$ | $0.3 \leq \omega \leq \pi$ | 1 |

**Selection of Order**

Predator prey optimization algorithm is hybridized using hooke jeeves exploratory move and opposition based learning. The results have been taken by varying order of filter. Order of filter has been varied from 20 to 50 and the best objective function has been evaluated. Fig.1 shows the objective function variations with respect to order of filter.

Thus it is observed that filter order 44 has been selected as best order for designing low pass digital FIR filter having minimum objective function.

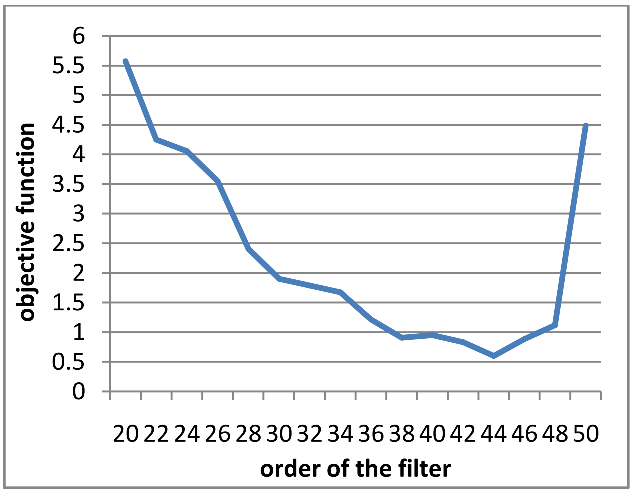


Figure.1 Objective Function v/s Order of Filter

HPPO algorithm has the capability of giving enhanced performance than other algorithms at higher orders. HPPO proves itself superior in terms of objective function, magnitude errors. The objective function, magnitude errors and pass band and stop band performance at different filter orders are depicted in Table 2.

Table 2: Design of Low Pass FIR Filter for Different Orders

| **Sr. No.** | FILTER ORDER | OBJECTIVE FUNCTION |
|---|---|---|
| 1. | 20 | 5.576775 |
| 2. | 22 | 4.250972 |
| 3. | 24 | 4.054890 |
| 4. | 26 | 3.547755 |
| 5. | 28 | 2.408923 |
| 6. | 30 | 1.900710 |
| 7. | 32 | 1.789094 |
| 8. | 34 | 1.675526 |
| 9. | 36 | 1.217000 |
| 10. | 38 | 0.910387 |
| 11. | 40 | 0.952614 |
| 12. | 42 | 0.834252 |
| 13. | 44 | 0.601866 |
| 14. | 46 | 0.888475 |
| 15. | 48 | 1.120230 |
| 16. | 50 | 4.488322 |


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ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

The performance of this algorithm is improved by varying various parameters such as order of filter, population size, and acceleration constants.

**Selection of Population Size**

The Fig. 2 shows objective function variations with respect to population size. Population has been varied from 60 to 140 in steps of 20 for filter order 44 using the HPPO algorithm. The value of objective function slightly changes from population 60 to 80 and after that there is abrupt change in value of objective function. The minimum value of objective function is observed at population size 60.

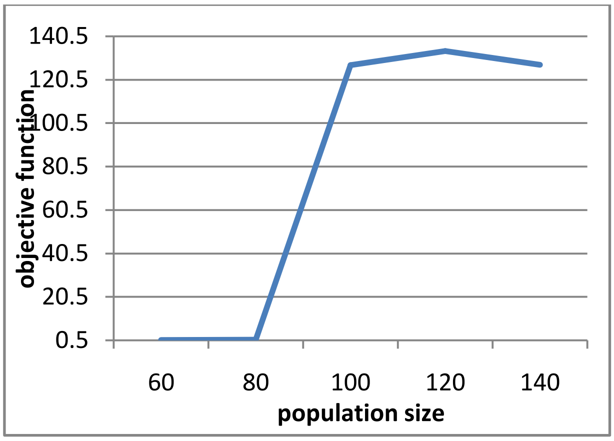


Figure.2 Population Size v/s Objective Function for Filter Order 44 Using HPPO

**Selection of acceleration constants ($c_1$ & $c_2$)**

The values of acceleration constants vary from 0.5 to 2.5 in steps of 0.5 for digital FIR filter design using HPPO. Minimum value of objective function observed at constants equal to 2.5. It is observed from Fig. 3 that the objective function gradually decreases from acceleration constant 1 to 2. Then the value of acceleration constants slightly decreases and then again increases. So order 44 with $c_1$ and $c_2$ equal to 2.5 has the minimum value of objective function.

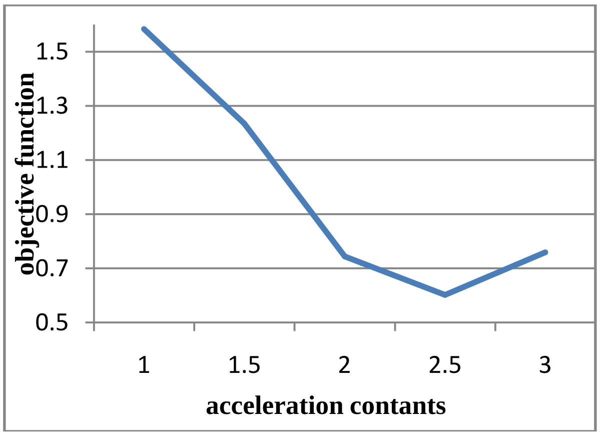


Figure.3 Objective Function v/s Acceleration Constants ($c_1$ & $c_2$) for Filter Order 44 Using HPPO

**Analysis of Magnitude and Phase Response of Low Pass Digital FIR Filter**

Order of filter is taken as 44 which results in 45 numbers of coefficients. Only half coefficients have been computed because of the symmetry property of FIR filter. Table. 3 show the calculated coefficients.

Table 3: Optimized Filter Coefficients

| Sr. No. | h(z) | Coefficient value |
|---|---|---|
| 1. | h(0)=h(23) | -.001701 |
| 2. | h(1)=h(24) | -.002803 |
| 3. | h(2)=h(25) | -.001559 |
| 4. | h(3)=h(26) | .002079 |
| 5. | h(4)=h(27) | .005913 |
| 6. | h(5)=h(28) | .006632 |
| 7. | h(6)=h(29) | .002353 |
| 8. | h(7)=h(30) | -.005596 |
| 9. | h(8)=h(31) | -.012303 |
| 10. | h(9)=h(32) | -.012330 |
| 11. | h(10)=h(33) | -.002969 |
| 12. | h(11)=h(34) | .012088 |
| 13. | h(12)=h(35) | .023733 |
| 14. | h(13)=h(36) | .022104 |
| 15. | h(14)=h(37) | .003382 |
| 16. | h(15)=h(38) | -.025433 |
| 17. | h(16)=h(39) | -.047797 |
| 18. | h(17)=h(40) | -.044442 |
| 19. | h(18)=h(41) | -.003706 |
| 20. | h(19)=h(42) | .070449 |
| 21. | h(20)=h(43) | .157308 |
| 22. | h(21)=h(44) | .227041 |
| 23. | h(22) | .253716 |

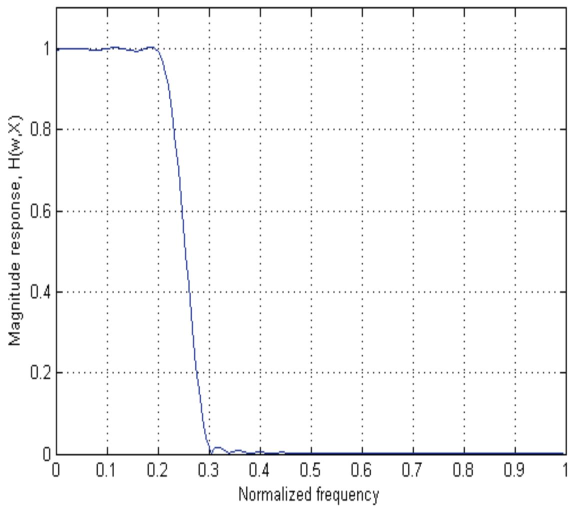


Figure.4 Plot of Magnitude Response v/s Normalized Frequency for Filter Order 44 Using HPPO

The Fig. 4 shows the graph for absolute magnitude response of order 44 for low pass digital FIR filter. Fig. 5 depicts the plot between absolute magnitude response in

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

dB and normalized frequency for order 44 for the design of low pass FIR filter.

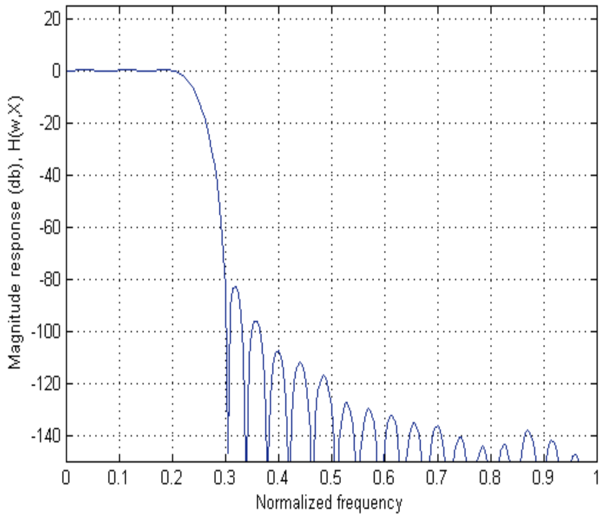


Figure.5 Plot of Magnitude Response in dBI v/s Normalized Frequency for Filter Order 44 Using HPPO

The graph between absolute phase response and normalized frequency for order 44 for the design of low pass FIR filter has been shown in Fig. 6.

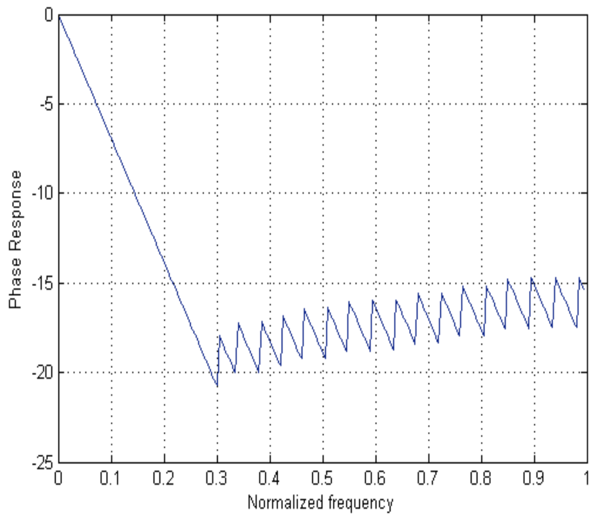


Figure.6 Plot of Phase Response v/s Normalized Frequency for Filter Order 44 Using HPPO

Here, the performance of HPPO compared with HDE performance in terms of objective function, magnitude errors and pass band ripple. HDE is an evolutionary algorithm that contains the features of both i.e. basic DE and exploratory move. DE has the capability to explore the search space globally and can also handle non linear and non differentiable cost function. Exploratory move used to search the local neighbourhood of global solution. In Hybrid Differential Evolution (HDE), it is observed that at order 44 the value of objective function [10] is 0.0694658, but in HPPO the value of objective function at order 44 is 0.601866, which is less. The comparison of other parameters is shown in Table 4 as below.

Table 4: Summary of HPPO Results with Hybrid DE Algorithm for FIR Low Pass Filter of Order 44

| Algorithm | HDE [10] | HPPO |
|---|---|---|
| Objective Function | 0.694658 | 0.601866 |
| Magnitude Error 1 | 0.427289 | 0.336910 |
| Magnitude Error 2 | 0.045880 | 0.043773 |
| Pass Band Performance | 0.029392 | 0.009635 |
| Stop Band Performance | 0.007026 | 0.015917 |

Table 4 Shows that Hybrid Predator Prey Optimization (HPPO) yields better results than Hybrid Differential Evolution (HDE) algorithm in terms of objective function, magnitude errors and pass band ripple. But due to conflicting nature of pass band and stop band ripples; HPPO has greater value of stop band ripple than HDE algorithm. So it is observed that HPPO gives better results than HDE algorithm.

## V. CONCLUSION

This paper presents the combination of predator prey optimization, hooke jeeves exploratory move and opposition based learning for low pass digital FIR filter design problem. This HPPO algorithm enhances the capability to explore the search space locally as well globally to obtain the optimal filter design parameters. HPPO has a much improved version then other filter designing techniques. In this paper filter of order 44 have been realized using HPPO algorithm. Then two control parameters i.e. population size and acceleration constants $C_1$ and $C_2$ have been varied in order to obtain better results. It has been concluded that best results are obtained with population size 60 and value of acceleration constants $C_1$ & $C_2$ equals to 2.5. From simulation results it is concluded that, HPPO shows better performance in terms of objective function, pass band ripple and magnitude errors than HDE. HPPO method is effectively applied for the design of low pass, high pass, band pass and band stop digital FIR filters.

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ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 8, August 2016

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