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An Optimized FIR Filter Design using Particle Swarm Optimization

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ABSTRACT

In this paper, algorithms are proposed to design optimal Finite Impulse Response (FIR) filters using variants of Biogeography based optimization (BBO) and particle swarm optimization (PSO) techniques. The proposed hybrid BBO-PSO algorithm is applied for determining optimal FIR filter coefficients. The algorithm is activated to design all four types of FIR filters- Low pass(LP), High pass(HP), Band pass(BP) and Band stop(BS).The order of filter for design is taken as 20 and hence the number of coefficient is 21.The number of samples per frequency is 128 and the sampling frequency is 1Hz. The optimal parameters chosen for the operation of proposed hybrid BBO-PSO algorithm are pass band ripple and stop band ripple. The simulation is carried out in MATLAB and executed in a PC with i5 processor with 3.5GHz speed. Thus the proposed hybrid BBO-PSO proves to compute optimal filter co-efficient with minimal execution time and attaining faster convergence rate. The numerical simulation results proves that the proposed two Variants of BBO-PSO results in better performance with respect to magnitude responses maximum stop band attenuation, lowest stop band ripples with decreased transition width.

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INTRODUCTION

Digital filter plays an important role for low power digital signal processing applications. The FIR filter is one of the most fundamental processing elements in any digital signal processing (DSP) system. The key application of these digital filters are restoring the signal and separating the signal. Signals are to be separated when the signal consists of added noise along with them and the signals are to be restored when it has got distorted. Basically a digital filter is implemented when the digital filter's impulse response is convoluted with that of the input signal. Using this modality, all the combinations are made to realize the digital filter to meet the desired specifications. Also, the digital filters can be realized employing recursive techniques. The weighted input samples will be added together to compute each samples of the output when the digital filter is designed using convolution approach.

In case of recursive filters, the general impulse responses are comprised of sinusoids which make the amplitude get decayed exponentially. Due to this fact, there exist infinitely long impulse responses. Also, the amplitude of the response will get reduced below the round-off noise of the considered system and as a result, the existing other samples will be omitted. Due to this feature, recursive filters are termed as Infinite Impulse Response (IIR) filters. But the filters developed using convolution approaches are termed as Finite Impulse Response (FIR) filters. There exists no feedback for FIR filter and as a result they are stable by nature. When 'n' is the order of the filter, FIR filters denote the output samples to be the weighted sum of the last 'n+1' inputs. Existence of symmetrical coefficients makes the linear phase filter and this will lead to the delaying of signals of the complete frequencies in an equal manner. Designing of FIR filters are easier than that of the design of IIR filters. Basically, various types of windowing techniques are employed to meet the desired window specifications. The purposes of windows are to approximate the infinite length of the basic ideal filter impulse response to a finite window for designing the actual response. But these conventional techniques do not have adequate and exact control of the different frequencies like – stop band cut-off frequency, pass band cut-off frequency and the transition width.

To possess enough control over the frequencies of the designed filter, this paper proposes variants of Biogeography based optimization technique to design optimal FIR filters to meet the desired specifications.

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Related works:

Parks & McClellan 1972 proposed the earlier Chebyshev procedures for carrying out the design of the filter and it was called Parks – McClellan (PM) algorithm. Numerous conventional methods proposed had the problem to get hanged with local minima, because of the fact that they are dependent on the initial solutions. In general for traditional optimization techniques to be employed on the objective functions, it is necessary that the chosen objective function should be in continuous and differentiable form. The limitations of conventional techniques for design of optimal filter include the algorithm complexity and the speed with which it converges. The objective function employed for designing optimal filters has precise control over the frequency spectrum parameters and as a result they are highly non-linear, non-uniform, non-differentiable and are multi modal. Conventional optimization approaches do not possess the means to handle the objective functions of high non-linearity and non-uniformity as well that are non-differentiable and does not converge to obtain the global solution.

To overcome all the limitations discussed above and faced by conventional techniques, many researchers have applied variety of meta-heuristic and heuristic evolutionary optimization algorithms based on nature inspiration to design optimal linear digital filters. These evolutionary optimization approaches starts with Genetic Algorithm (Ahmad & Antoniou 2006), Differential Evolution (Liu *et al* 2010), Artificial Neural mechanism (Van den Bergh & Engel Brecht 2000), Bee Colony Optimization (Karaboga 2009) and other animal based behavior approaches (Cuevas 2012) and so on. For digital filter design, over the decades it has been observed that GA provides a good solution, but they have proved their inefficiency in determining their global optimum with respect to the solution quality and convergence of speed. To overcome the shortfall of standard GA as said above, other methodologies were proposed – Particle Swarm Optimization (PSO) (Najjarzadeh & Ayatollahi 2008), Adaptive Differential Evolution (Pan 2011), Other variants of PSO (Fang et 2006, Luitel & Venayagamoorthy 2010, Sarangi *et al* 2011, Yu *et al* 2009, Mondal *et al* 2011), Gravitational Search Algorithm (Rashedi *et al* 2011), various hybrid algorithms(Luitel & Venayagamoorthy 2008).

On a whole, from the literature studies carried out it has been observed that there exist problems for assigning control parameters of the algorithms, premature convergence and the same solution is been arrived repeatedly. This work focuses on efficient and effective FIR filter design employing proposed optimization techniques. The proposed algorithm in this work involves the hybridized approach of Biogeography Based Optimization (BBO) (Simon 2008) and PSO (Kennedy & Eberhart 1995, 2001), merging the essential characteristics of both the heuristic algorithms. In this approach, BBO involves mutation operation which makes the problem getting stuck with the repeated same solution, at this point PSO is invoked which explores the solution to reach optimal FIR filter parameters.

Problem definition:

Fundamentally, the major classification of digital filters fall into two types – Infinite Impulse Response (IIR) filters and Finite Impulse Response (FIR) filters. The implementation of FIR filters and their hardware realization is easier than that of the IIR filters. As a result, in this paper, work is carried out to determine the optimal filter coefficients of FIR filters. With respect to the basic concepts from the literature, it is well known that, the impulse response of FIR (Oppenheim *et al* 1999) filter is given by,

$$H(z) = h(0) + h(1)z^{-1} + h(2)z^{-2} + h(3)z^{-3} + \ldots + h(N)z^{-N} \quad i.e.,$$

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

Where h(n) represents the impulse response of the filter. For the FIR filter case, the difference equation of the impulse response is given by,

$$y(n) = h(0)x(n) + h(1)x(n-1) + \ldots + h(N)x(x-N) \tag{2}$$

Where the order of the filter is N and the number of filter coefficients is N+1.

The objective of the optimization algorithm is to compute the values of impulse responses h(n). It is well known that the values of impulse responses will decide the type of FIR filter it falls into like – Low Pass (LP), High Pass (HP), Band Pass (BP) and Band Stop (BS). The algorithms are proposed in this paper to optimally design the four types of filters with the specifications considered being flat pass band, distortion factor to be low, highest stop band attenuation and minimal transition width.

During the process flow of the proposed algorithm, these particles which represents h(n) gets updated. The fitness values as given by equation (5) are computed for each of the new h(n) coefficients during the progress of iteration. The iteration is carried out until the maximum numbers of specified iterations are completed or the final fitness value reaches a specified lower value. The key feature of design of linear phase FIR filter is that the coefficients are symmetrical in nature. The proposed algorithms attempts to update only the half of the coefficients and further they are concatenated to obtain the complete h(n) sequence. As a result, the computational complexity is reduced and the dimensionality of the problem is made half. The optimal filter coefficients are computed using the proposed hybrid BBO – PSO and are compared with that of the earlier literature based heuristic evolutionary algorithms used for computing FIR filter coefficients (Saha *et al* 2013).

The FIR filter frequency response can be computed by,

$$H(\omega_k) = \sum_{n=0}^{N} h(n) e^{-j\omega_k n} \tag{3}$$

Where $\omega_k = (2\pi k / N)$ and the Fourier transform is given by $H(\omega_k)$. Considering $H_d(\omega)$ and $H_i(\omega)$ representing the magnitude response of the designed and ideal filters, the responses of each of the filters in ideal case is given in Table 1.

Table 1: Magnitude Responses of LP, HP, BP and BS FIR filters.

Sl.No	Type of Filters	Magnitude Response for ideal case
1.	Low Pass Filter	$\begin{cases} 1 & for\ 0 \le \omega \le \omega_c \\ 0 & otherwise \end{cases}$
2.	High Pass Filter	$\begin{cases} 0 & for\ 0 \le \omega \le \omega_c \\ 1 & otherwise \end{cases}$
3.	Band Pass Filter	$\begin{cases} 1 & for\ \omega_{pl} \le \omega \le \omega_{ph} \\ 0 & otherwise \end{cases}$
4.	Band Stop Filter	$\begin{cases} 0 & for\ \omega_{pl} \le \omega \le \omega_{ph} \\ 1 & otherwise \end{cases}$
ω_c – cut off frequencies of high pass and low pass filters ω_{pl} and ω_{ph} – lower and upper pass band/ stop band edge frequencies for the band pass and band stop filters.		

Objective function or fitness function plays a major role in any of the optimization techniques to determine solution thereby leading to convergence. In case of digital filter design, the fitness function used is an error function given by Parks – McClellan (PM) algorithm (Parks & McClellan 1972) as follows,

$$E(\omega) = G(\omega)[H_d(e^{j\omega}) - H_i(e^{j\omega})] \tag{4}$$

Here G(ω) is the weighting function which aids to provide various weights to approximate errors in different frequency bands. The main limitation of this PM algorithm is that the ratio of pass band and stop band ripple is fixed. As a result, the error function of PM algorithm is re-modified to overcome the fixed value of the ratio of pass band and stop band and is given by,

$$F_{df}(\omega) = \sum abs[abs(|H(\omega)| - 1) - \delta_{pf}] + \sum abs[abs(|H(\omega)| - \delta_{sf})] \tag{5}$$

For the above equation (5), in first part the value of ω belongs to a pass band including the portion of the transition band and in case of second part; the value of ω belongs to a stop band including the remaining portion of the transition band. The selection of transition band portions depends on the pass band and stop band edge frequencies. Thus in this paper equation (5) is used as the fitness function to compute the optimal FIR filter coefficients to design the filter. The aim of the proposed algorithm is to minimize this equation (5) to the ulterior lowest level. This fitness function performs computation of all the sums of the absolute errors for the complete frequency band and thus minimizes of this function results in reducing stop band ripples and increasing stop band attenuation and as well transition width also gets decreased.

Proposed Hybrid BBO – PSO algorithm for digital FIR filter design:

This section presents the proposed Hybrid BBO – PSO algorithm developed with an aim to achieve better FIR filter (LP, HP, BP and BS) coefficients by minimizing the fitness function given in equation (5).

Biogeography Based Optimization (BBO):

Biogeography is the concept of how species migrate from one island to another, how new species arise, and how species become extinct. As a well known fact, a habitat is any Island (area) that is geographically isolated from other Islands. Habitats with a high HSI (High Suitability Index) tend to have a more number of species, while those with a low HSI have a small number of species. Habitats with a high HSI have a low species immigration rate because they are already nearly saturated with species. By the same token high HSI habitats have a high emigration rate. Habitats with a low HSI have a high species immigration rate because of their sparse populations. Emigration in BBO does not mean that the emigrating island loses a feature. The worst solution is assumed to have the worst features; thus, it has a very low emigration rate and a low chance of sharing its features. The solution that has the best features also has the highest probability of sharing them. This approach is known as biogeography based optimization (Simon 2008, Aniruddha & Pranab 2010).

Mathematically the concept of emigration and immigration can be represented by a probabilistic model. Let us consider the probability P_S that the habitat contains exactly S species at t. P_S changes from time t to time $t+\Delta t$ as follows:

$$P_S(t+\Delta t) = P_S(t)(1-\lambda_S \Delta t - \mu_S \Delta t) + P_{S-1}\lambda_S \Delta t + P_{S+1}\mu_{S+1}\Delta t \tag{6}$$

where λ_S and μ_S are the immigration and emigration rates when there are S species in the habitat. This equation holds because in order to have S species at time $(t+\Delta t)$, one of the following conditions must hold: there were S species at time t, and no immigration or emigration occurred between t and $(t+\Delta t)$; there were $(S-1)$ species at time t, one species immigrated; there were $(S+1)$ species at time t, one species emigrated.

If time Δt is small enough so that the probability of more than one immigration or emigration can be ignored and as $\Delta t \to 0$ gives the following equation:

$$\dot{P}_S = \begin{cases} -(\lambda_S+\mu_S)P_S + \mu_{S+1}P_{S+1} & S=0 \\ -(\lambda_S+\mu_S)P_S + \lambda_{S-1}P_{S-1} + \mu_{S+1}P_{S+1} & 1 \le S \le S_{max}-1 \\ -(\lambda_S+\mu_S)P_S + \lambda_{S-1}P_{S-1} & S = S_{max}. \end{cases} \tag{7}$$

The equation for emigration rate μ_k and immigration rate λ_k for k number of species can be written as per the following way:

$$\mu_k = \frac{E_k}{n} \qquad \lambda_k = I\left(1-\frac{k}{n}\right) \tag{8}$$

When the value of $E=I$, then combining the above said equation, it results in,

$$\mu_k + \lambda_k = E_k \tag{9}$$

In BBO, there are two main operators, the migration and the mutation. It can be noted that the mutation rate changes the habitat's Suitability Index Variable (SIV) in a random manner based on the mutation rate. Also, the mutation rate will be inversely proportional to the probability of species – count. With the migration operator, BBO can share the information among solutions. Especially, poor solutions tend to accept more useful information from good solutions. This makes BBO be good at exploiting the information of the current population.

Particle Swarm Optimization:

Particle Swarm Optimization is a population based stochastic optimization technique developed by Kennedy and Eberhart (1995) inspired by social behavior of bird flocking or fish schooling. The PSO method is a member of the wide category of Swarm Intelligence methods. In PSO, the system is initialized with a population of random solutions and searches for optima by updating generations. During the process of PSO, the potential solutions, called particles, which are a metaphor of birds in flocks, fly through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations.

In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far (The fitness value is also stored). This value is called personal best and is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest. After finding the two best values (pbest and gbest), the particle updates its velocity and positions. The algorithmic steps involved are as follows (Kennedy and Eberhart 2001):

Step 1: Initialization: For each particle initialize its particle values randomly.

Step 2: Fitness Evaluation:

For each particle,

i) Calculate the fitness value

ii) If the fitness value is better than the best fitness value (pbest) in history so far,

Set current value as the new pbest.

End

Step 3: Global Best Selection:

Choose the particle with the best fitness value of all the particles as the gbest.

Step 4: Velocity and Position Updation:

For each particle

i) Calculate particle velocity

$$v_i = w * v_i + c_1 R_1 (p_{i\,best} - p_i) + c_2 R_2 (g_{ibest} - p_i) \quad (10)$$

where,

v_i – velocity of particle i

p_i – position of particle i

p_{ibest} - position with the 'best' fitness value found so far by particle i.

g_{ibest} - best fitness value obtained so far by any particle in the entire population

R_1, R_2 - random variables in the range [0, 1]

c_1, c_2 - learning factors controlling the related weighting of corresponding terms.

The inclusion of random variables endows the PSO with the ability of stochastic searching. The learning factors c_1 and c_2, compromise the inevitable trade-off between exploration and exploitation. After updating, v_i should be checked and secured within a pre-specified range to avoid violent random walking.

ii) Update particle positions

$$p_i = p_i + v_i \quad (11)$$

The position of all particles is updated according to equation (11).

Step 5: Termination checking:

The algorithm repeats steps 2 to 4 while maximum iterations or minimum error criterion is not attained. Once terminated, the algorithm reports the values of gbest and its respective fitness value.

The flowchart depicting the process of PSO algorithm is as shown in Figure 1.

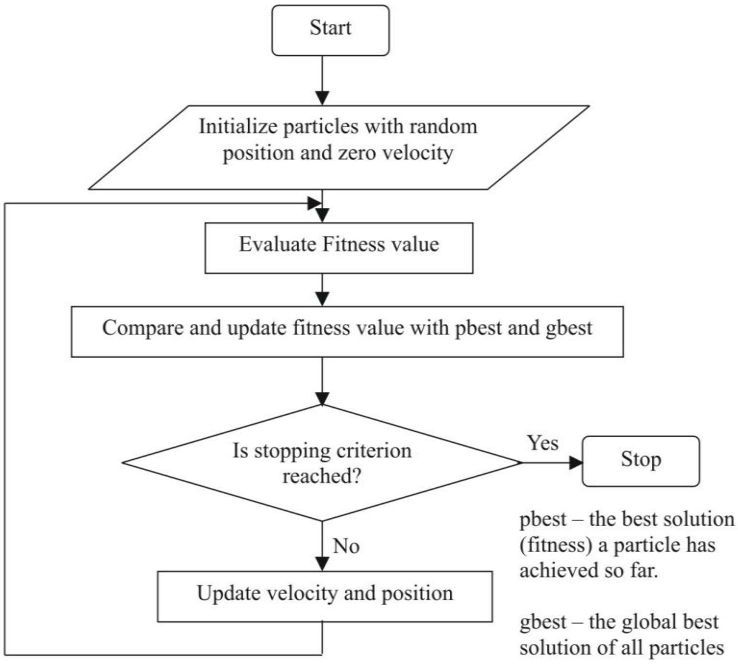

Fig. 1: Flowchart for Basic PSO Algorithm.

Proposed Hybrid BBO – PSO Algorithm:

In BBO process, as the habitat suitability index play a major role, the location of the species is identified based on the HSI value. During the flow of migration, if the transfer of species involving decision making gets oscillated, this might increase the convergence time and mutation process in BBO helps to identify or locate new species which results in improved fitness value. Henceforth the lack of BBO algorithm in its migration point will be handled by initiating PSO algorithm to result in faster convergence with better solution. Once the PSO is invoked at the migration point, the species will be searched by updating their movements through the velocity and position motion and the best global fitness would be arrived. If required after the PSO process is completed, then the BBO mutation process may be restarted to generate a new species and repeat the procedure for the specified number of iterations to obtain the solution. Introducing the PSO module during the migration process of BBO has developed a new algorithm known as Hybrid BBO – PSO. The structure of proposed hybrid BBO – PSO is simple in nature and the pseudo code for the proposed algorithm is as given in Table 2.

Table 2: Pseudo Code for Proposed Hybrid BBO – PSO Algorithm.

Start
Initialize the population randomly.
Compute the fitness and sort the population from best to worst.
Initialize probability of species count of each Habitat
When The termination criteria is not met do
Save the best habitats in a temporary array (Elitism)
For each habitat, map the Habitat Suitability Index (HSI) to number of species S,λ and μ
Choose the immigration island based on μ
Migrate randomly selected SIVs based on the selected island in previous step.
Invoke PSO:
Take the current population to be the point at which best fitness occurred and initiate the process
Perform Velocity updation and position updation
Take the particles for the evaluated position updates
Mutate the particles probabilistically using basic BBO mutation process
Compute the fitness and sort the population from best to worst.
Perform the checking condition
Refine the habitats
end if
Sort the population
Check for feasible solution and the presence of a similar habitat
Stop

Numerical examples and results using proposed hybrid BBO – PSO Algorithm:

The proposed hybrid BBO – PSO algorithm is applied for determining optimal FIR filter coefficients in this section. The algorithm is activated to design all four types of FIR filters – LP, HP, BP and BS. The order of filter for design is taken as 20 and henceforth the number of coefficients is 21. The number of samples per frequency is 128 and the sampling frequency is 1 Hz. The optimal parameters chosen for the operation of hybrid BBO- PSO algorithm is tabulated in Table 3. The parameter of the filter to be designed using the proposed algorithm are: pass band ripple (δ_{pf}) = 0.1 and stop band ripple (δ_{sf}) = 0.01.

Table 3: Parameters of Hybrid BBO – PSO Algorithm.

Parameters	BBO	Parameters	PSO
Habitat Size	50	Particle Size	50
Habitat Modification probability	1	Acceleration constants c_1 and c_2	1.5
Immigration Probability bounds per gene	[0,1]	w_{min}	0.4
Step size for numerical integration	1	w_{max}	1.0
Maximum Immigration	1	v_i^{max}	1.0
Migration rate for each island	1	v_i^{min}	0.01
Mutation probability	0.005		
Maximum Iteration	500	Maximum Iteration	500
Filter Coefficients Limits	-2 to +2	Filter Coefficients Limits	-2 to +2

The normalized filter coefficients considered for each of the filters FIR LP, HP, BP and BS for simulating the proposed algorithm is as given in Table 4.

The proposed algorithm is tuned to compute the optimal filter coefficients with the normalized filter coefficients as given in Table 4 and with the algorithmic parameters as stated in Table 3. The simulation is carried out in MATLAB R2012a and executed in a PC with Intel core i5 processor with 3.5 GHz speed and 10GB RAM with 64 bit operating system. Table 5 to Table 8 shows the optimal FIR filter coefficients of LP, HP, BP and BS filters tuned using the proposed hybrid BBO – PSO algorithm and as well the values computed for the other evolutionary algorithms taken from the literature studies (Ababneh & Bataineh 2008, Karaboga *et al* 2006, Luitel & Ganesh 2008).

Table 4: Normalized filter coefficients considered for design of filters.

Parameters	FIR LP filter	FIR HP filter	Parameters	FIR BP filter	FIR BS filter
Pass Band edge frequency	0.45	0.55	Lower pass band edge frequency	0.35	0.25
			Lower stop band edge frequency	0.25	0.35
Stop Band edge frequency	0.55	0.45	Upper pass band edge frequency	0.65	0.85
			Upper stop band edge frequency	0.75	0.75
Transition width	0.1	0.1	Transition width	0.1	0.1

Table 5: Optimized FIR LP filter coefficients of order 20

h(N)	Genetic algorithm (GA) (Ababneh & Bataineh 2008)	Particle Swarm Optimization (Ababneh & Bataineh 2008)	Differential Evolution (DE) (Luitel & Ganesh 2008)	Proposed Hybrid BBO - PSO
h(1) =h(21)	0.020644508012550	0.025116793352393	0.027005399982491	0.029786567321905
h(2) =h(20)	0.048721413185106	0.047219259300299	0.047266866797926	0.048564321890321
h(3) =h(19)	0.005868601564964	0.003546242723169	0.005320204222841	0.005974329012781
h(4) =h(18)	-0.040966865300227	-0.040094047283599	-0.038982294859373	-0.034873216589362
h(5) =h(17)	-0.000863506780022	-0.000520432067214	-0.003452235386096	-0.001341687231947
h(6) =h(16)	0.059796031265565	0.060907207778672	0.057946858872171	0.060134256187921
h(7) =h(15)	-0.001408842862974	-0.001759240756773	-0.002051400593964	0.003995439012678
h(8) =h(14)	-0.103117834700311	-0.103613994946693	-0.102715267629915	-0.102674390125431
h(9) =h(13)	-0.000440644382089	0.000627623037422	0.001692937801793	0.003114527829165
h(10)=h(12)	0.317600651261946	0.318119036548684	0.319795676258768	0.324562319876321
h(11)	0.500018538901556	0.500018538901556	0.500018538901556	0.504923981023332

Table 6: Optimized FIR HP filter coefficients of order 20.

h(N)	Genetic algorithm (Ababneh & Bataineh 2008)	Particle Swarm Optimization Ababneh & Bataineh 2008	Differential Evolution (Luitel & Ganesh 2008)	Proposed Hybrid BBO - PSO
h(1) =h(21)	0.021731353326545	0.025559145974814	0.029041921147266	0.029165732198021
h(2) =h(20)	-0.048131602227058	-0.047413653181042	-0.045873202416582	-0.045003267819287
h(3) =h(19)	0.006298189918824	0.005135430273491	0.002950561225606	0.003124567289032
h(4) =h(18)	0.041895345956760	0.039988099089174	0.041311799862169	0.042995463210943
h(5) =h(17)	0.000879943669486	0.001405996354021	-0.000283997158910	0.000099765432109
h(6) =h(16)	-0.059027866591514	-0.060283192968605	-0.060002355552046	-0.057354621987652
h(7) =h(15)	-0.000013559660394	0.000768613197325	-0.003921102337490	0.003276542109876
h(8) =h(14)	0.104257677520726	0.105120739785348	0.106119151142982	0.102976543109266
h(9) =h(13)	0.003823743541217	0.001471927911810	-0.000565063060302	-0.002498763452719
h(10)=h(12)	-0.316631427282300	-0.315471590838371	-0.320083906578923	-0.318762314902167
h(11)	0.499468012025621	0.499981461098444	0.499981461098444	0.499981461098444

Table 7: Optimized FIR BP filter coefficients of order 20.

h(N)	Genetic algorithm (Ababneh & Bataineh 2008)	Particle Swarm Optimization Ababneh & Bataineh 2008	Differential Evolution (Luitel & Ganesh 2008)	Proposed Hybrid BBO - PSO
h(1) =h(21)	0.028502857888104	0.024910907374264	0.024315759656957	0.029317654289013
h(2) =h(20)	-0.001893868108392	0.000092972958187	0.002788616388318	-0.002851243178650
h(3) =h(19)	-0.076189026154460	-0.074535581888545	-0.075883731240533	-0.075254309123718
h(4) =h(18)	0.000994123920259	-0.000579129089510	-0.003313368788351	0.003267654290146
h(5) =h(17)	0.053196793860741	0.058322287561503	0.056134992376798	0.051129870543219
h(6) =h(16)	-0.000639149080848	-0.000187613541059	0.000257826174027	0.001539876534210
h(7) =h(15)	0.100057194730152	0.093164875388599	0.090912344142406	0.100166529817532
h(8) =h(14)	0.001409980793664	0.001012723950710	0.002199187065772	-0.004987623415628
h(9) =h(13)	-0.299380312728113	-0.296866917983546	-0.300934749358008	-0.297865412093267
h(10)=h(12)	-0.000752480372393	-0.000392232750468	-0.001799401229551	0.002791324501876
h(11)	0.400369877077545	0.400369877077545	0.400369877077545	0.400369877077545

Table 8: Optimized FIR BS filter coefficients of order 20.

h(N)	Genetic algorithm (Ababneh & Bataineh 2008)	Particle Swarm Optimization Ababneh & Bataineh 2008	Differential Evolution (Luitel & Ganesh 2008)	Proposed Hybrid BBO - PSO
h(1) =h(21)	0.008765244188382	0.005065078955931	0.005738163937772	0.010123765189321
h(2) =h(20)	0.054796923249762	0.054496716662981	0.053905628215447	0.052578432109876
h(3) =h(19)	0.001796419983890	0.005809988516188	0.002902448937586	0.011983425167212
h(4) =h(18)	0.048911654246731	0.051144048751957	0.049349878942931	0.047987234140932
h(5) =h(17)	-0.054718457691943	-0.050663949788261	-0.050884656047053	-0.048342165789122
h(6) =h(16)	-0.060963142228236	-0.062741465298722	-0.063088550820316	-0.066432516821093
h(7) =h(15)	0.004293459264617	-0.000062718416445	0.004089341810059	-0.001019954326171
h(8) =h(14)	-0.065342448643273	-0.068916923681426	-0.068023108311494	-0.068716432145262
h(9) =h(13)	0.300682045893488	0.297478557865240	0.299063386928411	0.296970543219872
h(10)=h(12)	0.069036675664641	0.074390206250426	0.071701365941159	0.074352618711662
h(11)	0.499582536276171	0.499582536276171	0.500000357523254	0.500000357523254

Table 9 tabulates the maximum stop band attenuation of the designed LP, HP, BP and BS filters using the proposed hybrid BBO –PSO method and as well that of the other methods considered for comparison from the literature. Table 9 shows that the proposed approach yields the maximum stop band attenuation. Figure 2 shows the magnitude and phase response of the designed FIR LP, HP, BP and BS filters employing the proposed hybrid BBO –PSO approach.

Table 9: Stop band attenuation of the designed filters of order 2.

Filter type	Maximum stop band attenuation (dB)				
	PM (Park McClellan 1972)	GA (Ababneh & Bataineh 2008)	PSO (Ababneh & Bataineh 2008)	DE (Luitel & Ganesh 2008)	Proposed hybrid BBO – PSO
LP	23.56	26.11	28.03	29.53	34.12
HP	23.55	25.25	28.1	29.16	33.97
BP	22.37	30.8	32.03	32.58	35.01
BS	21.65	29.73	30.56	30.96	33.27

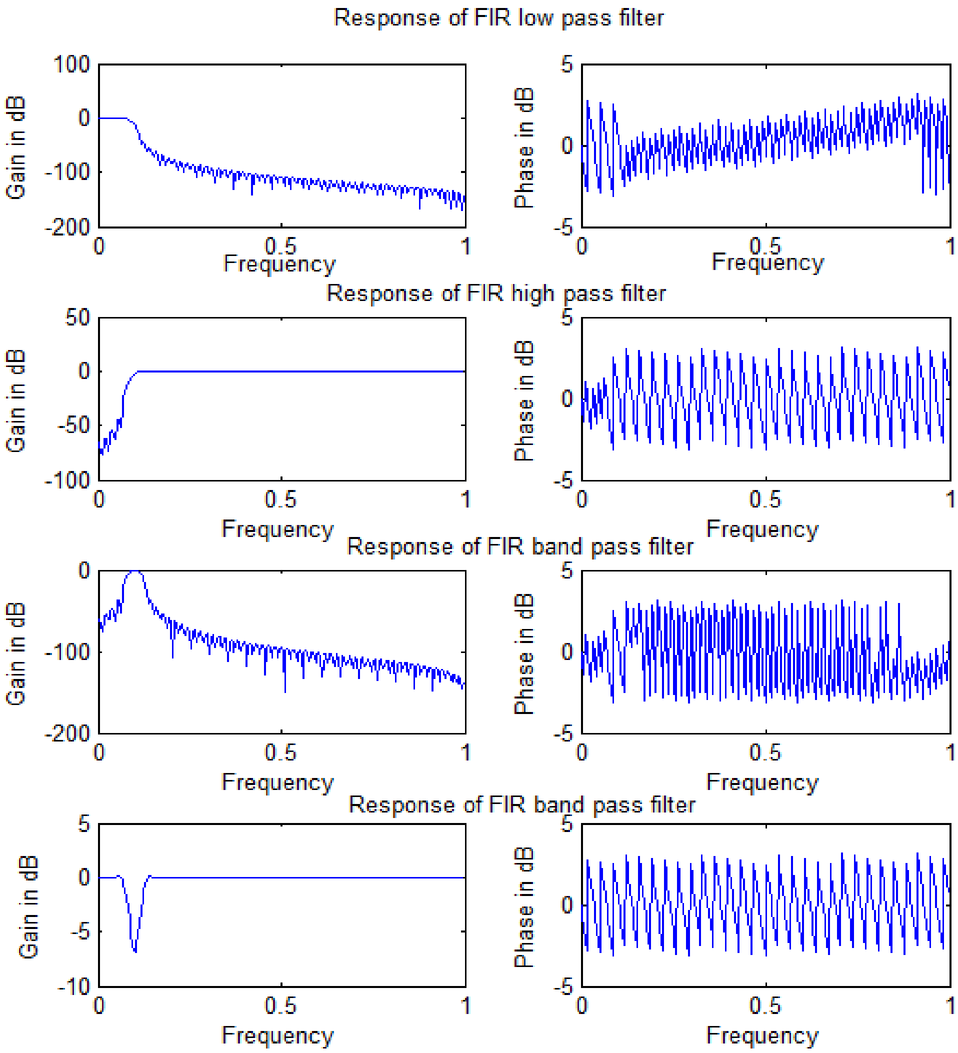

Fig. 2: Magnitude and Phase response of filter coefficients from proposed hybrid BBO – PSO.

From Table 9 it can be observed that the proposed hybrid BBO – PSO yields maximum stop band attenuation for all the filters and Table 5 to Table 8 infers that the response of the coefficients when taken i.e. the magnitude and phase response of the filter coefficients computed using hybrid BBO – PSO is better (Figure 2) when the response using the other methods (GA, PSO, DE) are computed. The response plots of the other methods GA, PSO and DE are obtained but are not shown in the Figure 2 due to the scaling problems of the plots. Thus the proposed hybrid BBO – PSO proves to compute optimal filter coefficients with minimal execution time and attaining faster convergence rate.

Conclusion:

This paper presents a novel proposed hybrid BBO – PSO for finding the solutions of the multi-modal optimal linear phase FIR filter coefficients identification and design problem with the specified constraints given. The proposed optimization algorithm is run on 500 iterations for 30 trials and the solutions were observed. The computed results of the proposed algorithms is verified and validated with that of the other existing algorithms employed for designing optimal Fir filter coefficients which includes GA, PSO and DE. Hence, the proposed BBO-PSO algorithm is validated to be a better global optimizer to obtain the optimal filter coefficients to design practical digital FIR filters for digital signal processing applications.

REFERENCES

Oppenheim, A.V., R.W. Schafer, J.R. Buck, 1999. Discrete-Time Signal Processing, Prentice Hall, Englewood Cliffs, NJ.

Ahmad, SU. and A. Antoniou, 2006. “A genetic algorithm approach for fractional delay FIR filters”. In:IEEE International Symposium on Circuits and Systems, ISCAS, pp: 2517–20.

Cuevas, E., M. Gonzalez, D. Zaldivar, M. Perez, GG. Torales, 2012. “An algorithm for global optimization inspired by collective animal behavior”, Discrete Dynamics in Nature and Society (DDNS); 638275, pp: 24.

Fang, W., J. Sun, W. Xu, J. Liu, 2006. “FIR digital filters design based on quantum-behaved Particle Swarm Optimization”, In:First International Conference on Innovative Computing, Information and Control, ICICIC ‘06(1): 615–9.

Karaboga, N., 2009. “A new design method based on artificial bee colony algorithm for digital IIR filters”, Journal of the Franklin Institute, 346(4): 328–48.

Kennedy, J. and R.C. Eberhart, 1995. ‘Particle Swarm Optimization’, Proceedings IEEE International Conference on Neural Networks, IEEE Service Centre, Piscataway, NJ, IV: 1942-1948.

Kennedy, J. and R.C. Eberhart, 2001. ‘Swarm Intelligence’, First Edition, Morgan Kaufman Publishers, San Francisco, California.

Liu, G., YX. Li, G. He, 2010. “Design of digital FIR filters using differential evolution algorithm based on reserved gene”, .In:IEEE congress on evolutionary computation, pp: 1–7.

Luitel, B., GK. Venayagamoorthy, 2008. “Differential evolution particle swarm optimization for digital filter design”, In:IEEE Congress on Evolutionary Computation, CEC, pp: 3954–61.

Luitel, B., GK. Venayagamoorthy, 2010. “Particle swarm optimization with quantum in fusion for system identification”, Engineering Applications of Artificial Intelligence, 23(5): 635–49.

Mondal, S., SP. Ghoshal, R. Kar, D. Mandal, 2011. “Optimal linearphase FIR Bandpass filter design using craziness based Particle Swarm Optimization Algorithm”, Journal of Shanghai Jiaotong University (Science), Springer, 16(6): 696–703.

Najjarzadeh, M., A. Ayatollahi, 2008. “FIR digital filters design: particle swarm optimization utilizing LMS and minimax strategies”, In IEEE International Symposium on Signal Processing and Information Technology,ISSPIT, pp: 129–32.

Pan, ST., 2011. “Evolutionary computation on programmable robust IIR filter pole- placement design”, IEEE Transactions on Instrumentation And Measurement, 60(4): 1469–79.

Parks, TW. and JH. McClellan, 1972. “Chebyshev approximation for non recursive digital filters with linear phase”, IEEE Transactions on Circuit Theory; CT, 19: 189–94.

Rashedi, E., N. Hossien, S. Saryazdi, 2011, “Filter modeling using gravitational search algorithm”, Engineering Applications of Artificial Intelligence, 24(1): 117–22.

Saha, SK., Sakti Prasad Ghoshal, Rajib Kar, Durbadal Mandal, 2013. “Cat Swarm Optimization algorithm for optimal linear phase FIR filter design”, ISA Transactions, 52: 781–794.

Sarangi, A., RK. Mahapatra, SP. Panigrahi, 2011. “DEPSO and PSO-QI in digital filter design”, Expert Systems with Applications, 38(9): 10966–73.

Simon, Dan, 2008, "Biogeography-based optimization." Evolutionary Computation, IEEE Transactions on, 12(6): 702-713.

Van den Bergh, F., AP. Engel brecht, 2000. “Cooperative learning in neural network using particle swarm optimizers”, South African Computer Journal, 26: 84–90.

Yu, X., J. Liu, H. Li, 2009. “An adaptive inertia weight Particle Swarm Optimization Algorithm for IIR digital filter”, In:International Conference on Artificial Intelligence and Computational Intelligence (AICI ’09), 1: 114–8.