EFFICIENT FIR FILTER DESIGN METHODOLOGY USING DYNAMIC REGIONAL HARMONY SEARCH ALGORITHM WITH OPPOSITION AND LOCAL LEARNING (DRHS-OLL)

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Abstract— In this paper, an optimal design of FIR filter is carried out using a "Dynamic Regional Harmony Search algorithm (DRHS) with Opposition and Local Learning". The Harmony Search (HS) is a robust optimization algorithm which mimics the musician's improvisation method and has been used by many researchers for solving and optimizing various real-world optimization problems and numerical solutions. For optimizing the functionality of the FIR filter, DRHS algorithm which is an enhanced variant of the HS algorithm is adopted to avoid pre-mature convergence and stagnation. BY adopting DRHS algorithm the low pass, high pass, band pass and band stop FIR filters are constructed and their performances are evaluated and compared with the other existing optimization techniques. A comparison of the DRHS with other optimization algorithms for constructing FIR filter clearly shows the DRHS finds the optimal solution and the convergence is clearly guaranteed.

Keyword- Harmony Search ,FIR Filter, Bio-inspired Optimization

I. INTRODUCTION

Digital filters are required to improve the quality of the signal by filtering the unwanted noise accompanied with the original signal. The quality of the filtered signal also depends on the quality of filtering which in turn is determined by the frequency response, phase response and linearity of the filter used [1]. Thus an appropriate FIR filter coefficients determines the overall performances in both the pass band and the stop band. To avoid the unwanted distortions in the filter performance, a high degree of linearity is intended in the phase response of the filter [2]. Thus the desired filter performance can be achieved by selecting suitable values of the filter coefficients and this can be achieved by most of the optimization algorithm already discussed in various papers. The conventional genetic algorithm (GA) uses a fixed chromosome length and hence finding an optimal solution is hard to realize with the fixed length [3 - 5]. The flexible genetic algorithm (FGA) overcomes this fixed length limitation further increasing the flexibility in the conventional GA [2] and it has the capability to optimize even complex and nonlinear problems involving multiple variables with constraints.

II. FIR FILTER DESIGN

The digital filters that can be categorized based on their impulse responses are;

- Infinite-extent impulse response (IIR) filters and
- Finite-extent impulse response (FIR) digital filters.

The FIR filter can be chosen when there is a strict requirement for a linear phase characteristics in the pass band region. It is known that the IIR filter has lower side lobes in the stop band region than an FIR filter with the same filter parameters. Hence an IIR filter can be chosen by the designer if a considerable amount of phase distortion owing to non-linearity is tolerable as it is advantageous in hardware perspective. Perhaps most of the real-time application demands a distortion less filtering and hence the design and optimization of FIR filters are considered[2].

The below difference equation describes the FIR filter with length M, input x(n) and output y(n) .

$$y(n)=b_0x(n)+b_1x(n-1)+...+b_{M-1}x(n-M+1) \tag{1}$$

$$y(n)=\sum_{k=0}^{M-1} b_k x(n-k) \tag{2}$$

Where, b_k is the set of filter coefficients. The impulse response of FIR filter is given by;

$$h(n)=\sum_{k=0}^{M-1} b_k \delta(n-k) \tag{3}$$

and the transfer function is given by ;

$$H(z)=\sum_{k=0}^{M-1} h(k) z^{-1} \tag{4}$$

An FIR filter has a linear phase if its impulse response satisfies the symmetry or anti-symmetry conditions [2]. $h(n) = \pm h(M-1-n), n = 0,1,....M-1$

After including the symmetry and anti-symmetry conditions in the above equation.

$$H(z) = z^{-(M-1)/2} \sum_{k=0}^{(M/2)-1} h(k)\left[z^{(M-1-2k)/2} \pm z^{-(M-1-2k)/2}\right]; M \text{ is } even \tag{5}$$

By substituting $z=e^{jw}$, the frequency response of the linear-phase FIR filter can be obtained as H(w). When h(n)=h(M-1-n), H(w) can be expressed as;

$$H(\omega)=H_r(\omega)e^{-j\omega(M-1)/2} \tag{6}$$

where Hr(w) is a real function of w and it is expressed as;

$$\begin{aligned} H_r(\omega) &= h\left(\frac{M-1}{2}\right) + 2\sum_{k=0}^{(M-3)/2} h(k)\cos\omega\left(\frac{M-1}{2}-k\right) \; M \text{ is odd} \\ H_r(\omega) &= 2\sum_{k=0}^{(M/2)-1} h(k)\cos\omega\left(\frac{M-1}{2}-k\right) \; \text{M is even} \end{aligned} \tag{7}$$

The phase characteristic of the filter for both odd and even is;

$$\varphi(\omega)=\begin{cases} -\omega\left(\dfrac{M-1}{2}\right) & \text{if } H_r(\omega)>0 \\ -\omega\left(\dfrac{M-1}{2}\right)\pm\pi & \text{if } H_r(\omega)<0 \end{cases} \tag{8}$$

Thus, the FIR design involves finding the M coefficients h(n), n-1,2,…,M-1 from the filter specification to have the desired response. The important parameters which should be considered while designing FIR filters are:

- Pass band ripple
- Stop band ripple
- Pass band edge ripple
- Stop band edge ripple

The widely used FIR filter design techniques are;

- Window method, and
- Frequency sampling method

And the above methods find an approximate frequency response similar to the ideal FIR characteristics. The conventional optimization techniques cannot find optimal solutions satisfying all the design requirements of the FIR filter discussed earlier and there is a tradeoff between the discussed FIR filter parameters.

The frequency response of the FIR digital filter is given by;

$$H(e^{j\omega_k})=\sum_{n=0}^{N} h(n)e^{-j\omega_k n} \tag{9}$$

And $\omega_k = 2\pi k/N$, $H(e^{j\omega_k})$ or $H(\omega_k)$ is the Fourier transform. After the frequency sampling with N points in $[0,\pi]$;

$$H_d(\omega) = [H_d(\omega_1), H_d(\omega_2), H_d(\omega_3), \ldots, H_d(\omega_N)]^T \tag{10}$$

$H_i(\omega) = [H_i(\omega_1), H_i(\omega_2), H_i(\omega_3), \ldots, H_i(\omega_N)]^T$ and H_i is the magnitude response of the ideal filter Magnitude response of Low pass FIR filter (LPF) is,

$$H_i(\omega_k) = \begin{cases} 1 & for \quad 0 \le \omega \le \omega_c \\ 0 & otherwise \end{cases} \tag{11}$$

Magnitude response of High pass FIR filter (HPF) is,

$$H_i(\omega_k) = \begin{cases} 0 & for \quad 0 \le \omega \le \omega_c \\ 1 & otherwise \end{cases} \tag{12}$$

Magnitude response of Band pass FIR filter (BPF) is,

$$H_i(\omega_k) = \begin{cases} 1 & for \quad \omega_{pl} \le \omega \le \omega_{ph}; \\ 0 & otherwise \end{cases} \tag{13}$$

Magnitude response of Band stop filter (BSF) is,

$$H_i(\omega_k) = \begin{cases} 0 & for \quad \omega_{pl} \le \omega \le \omega_{ph}; \\ 1 & otherwise \end{cases} \tag{14}$$

N – number of samples, ω_k - Approximate actual filter to be designed. The various kinds of Error functions of fitness functions used in the literature are given in the equations 15, 16 and 17; [7, 8, 9, 6]

$$Error = \max\left\{ \sum_{i=1}^{N} \left[\left| \left| H_d(\omega_k) \right| - \left| H_i(\omega_k) \right| \right| \right] \right\} \tag{15}$$

$$Error = \left\{ \sum_{i=1}^{N} \left[\left| H_d(\omega_k) \right| - \left| H_i(\omega_k) \right| \right]^2 \right\}^{1/2} \tag{16}$$

$$E(\omega) = G(\omega)[H_d(\omega_k) - H_i(\omega_k)] \tag{17}$$

ω , the weighting function provides weights for the approximated errors in various frequency bands.

As equation 17 doesn't consider δ_p/δ_s ratio, the error function should be changed to accommodate both the pass band and stop band ripple. Hence the following fitness function can be considered. [10, 12]

$$J_1 = \max_{\omega \le \omega_p}\left(\left| E(\omega) \right| - \delta_p \right) + \max_{\omega \ge \omega_s}\left(\left| E(\omega) \right| - \delta_s \right) \tag{18}$$

- δp – pass band ripple,
- δs – stop band ripple,
- ωp – normalized pass band edge frequencies
- ωs – normalized stop band edge frequencies

The error fitness function described in [11] is utilized and inherited in [1], which can be used to achieve better transition width and pass band ripple and stop band attenuation. It is worth noting that the transition width depends on the pass band edge and stop band edge frequencies.

$$J_2 = \sum abs[abs(\left| H(\omega) \right| - 1) - \delta_p] + \sum [abs(\left| H(\omega) \right| - \delta_s)] \tag{19}$$

The focus is on maintaining a constant magnitude in the pass band and acceptable level of ripple in the stop band. Hence the evolved coefficients of FIR filter using the proposed optimization algorithm will maintain a flat pass band in the magnitude response when compared to other optimization algorithms.

III. Optimization Algorithm

A. GA and its Variants

Genetic Algorithm (GA) initially described by Goldberg [13] is a stochastic search and optimization algorithm which has the potential to solve many real-time problems. The crossover and the mutation operators are primarily used in GA to create offsprings from the parent chromosomes and the chromosomes can be binary bit patterns or real valued numbers. The crossover operator yields a resultant offspring OF after performing the crossover operation between the two parent chromosomes P1 and P2. Thus OF = r(P1-P2)+P1, where r is a random number ranges from 0 to 1.

For maximization problems, the fitness of P1 should be greater than the fitness of P2 and the other way for minimization problems. The mutation operator changes a portion of the chromosome string randomly and the amount of change is called the mutation rate which determines the convergence for various problems. Thus by performing the above said genetic operators various offsprings are produced and those offsprings are considered only if the fitness value of the child chromosome is greater than the parent else it will be discarded. Hence new generations of chromosomes are formed from the better chromosomes from the previous stage and discarding the others and this forms the selection operation. The iterative process can be terminated upon achieving the optimal solution or after the predetermined number of iterations.

B. PSO and its Variants

PSO is a flexible, robust population-based stochastic search / optimization technique with implicit parallelism, which can easily handle with non differential objective functions, unlike traditional optimization methods. PSO is less susceptible to getting trapped on local optima unlike GA, Simulated Annealing etc. Eberhart et al. developed PSO concept similar to the behaviour of a swarm of birds. PSO is developed through simulation of bird flocking in multi-dimensional space. Bird flocking optimizes a certain objective function. Each particle vector (bird) knows its best value so far (pbest). This information corresponds to personal experiences of each particle vector. Moreover, each particle vector h(n) knows the best value so far in the group (gbest) among pbests. Namely, each particle tries to modify its position using the following information:

- The distance between the current position and the pbest.
- The distance between the current position and the gbest.

Similar to GA, in PSO techniques also, real-coded particle vectors of population np are assumed. Each particle vector consists of components or sub-strings as required number of normalized filter coefficients, depending on the order of the filter to be designed.

C. HS algorithm and its variants

The performance of the HS algorithm primarily depends on the harmony memory which exploits the solution search space. Hence sufficient harmony memory needs to be initialized to make the random selection operator explore the complete search space [14]. The efficiency of the HS algorithm in solving multimodal problems is limited as the sub-optimal solutions will obstruct the harmony memory to move towards optimal solution and perhaps the HS algorithm sometimes suffers from stagnation during the search for optimal solution. Thus the HS is modified to dynamic regional harmony search (DRHS) algorithm which includes opposition-based learning [14, 15] and local search [14, 16, and 17]

D. Advantages of DRHS

The harmony memory used in DRHS opposition based learning will have a better search space. The HS is applied to the sub groups of the HM independently and it is regrouped at regular interval to avoid stagnation and premature convergence. Also an opposition harmony is created for each group and among the original and the opposition harmony, the best is chosen for updating the HM. Local search is also performed on the overall best harmonies.

E. Dynamic Regional Harmony Search with Opposition and Local Learning (DRHS-OLL)

The HS variants proposed by various authors improve the optimization performance in terms of best solution, runtime and convergence [18, 19, 20]. Perhaps few hybrids optimization algorithms which use HS along with other metaheuristic algorithms like differential evolution (DE) and particle swarm optimization (PSO) [21, 22]. The DRHS-OLL algorithm originally proposed by A.K.Qin and Florence Forbes is used for optimization as it fixes the deficiencies in other proposed algorithms.

1) Improved strategies in DRHS-OLL [14]:

- Only half of the HM is used to create the solution space and another half is used for opposition-based learning [15].
- The HM is regrouped in each iteration to avoid premature convergence.
- DRHS also generates an opposite harmony by applying HS-OL.
- Group memory is updated with one of the two harmonies.
- It reduces premature convergence and stagnation

Also the local searches done by DRHS-OLL periodically enable robust optimization.

IV. EXPERIMENTS AND SIMULATION RESULTS

By adapting the DRHS-OLL the coefficients of the widely used four types of filters, namely LPF, HPF, BPF and BSF are optimized and the results are compared with other optimization techniques like PSO and HS-OL.

A. LPF

The magnitude response of the LPF is shown in Fig. 1a and the magnified pass band and stop band are shown in Fig. 1b and 1c respectively. The normalized cut-off frequency is chosen as 0.5 and the optimal order of the

FIR filter is found to be 36 for more efficient filtering. Fig. 1d shows the linear phase response of the FIR filters with optimized coefficients using various optimization algorithms.

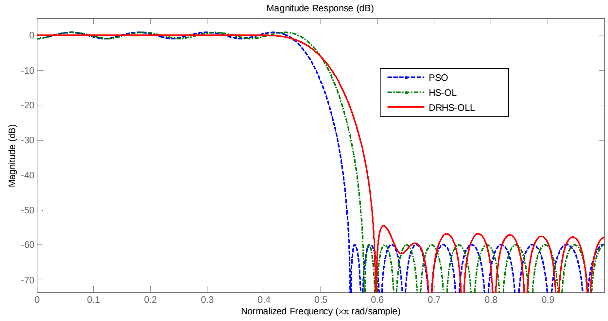

Fig. 1a: Magnitude response of LPF

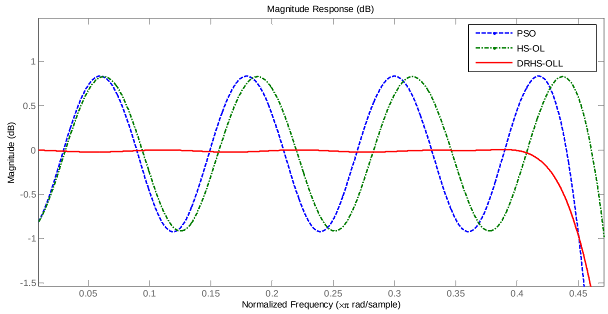

Fig. 1b: Magnified view of passband in magnitude response of LPF

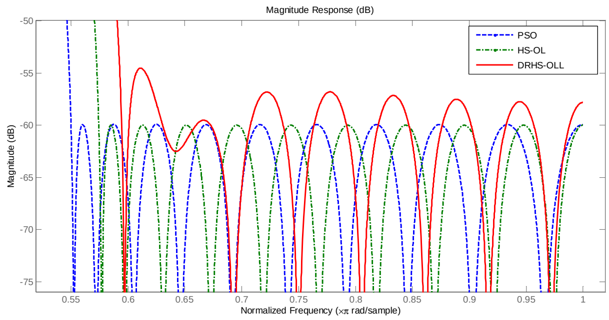

Fig. 1c: Magnified view of stopband in magnitude response of LPF

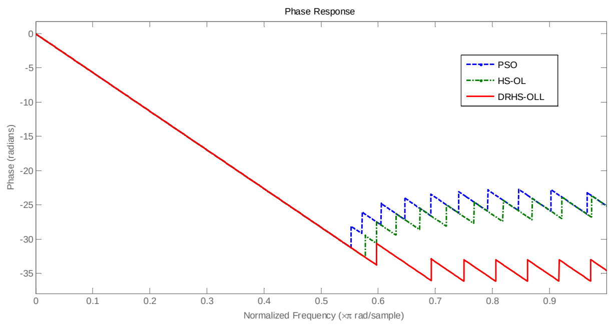

Fig. 1d: Phase response of LPF

The Table I lists the Low pass FIR filter coefficients of the three optimization techniques namely PSO, HS-OL and DRHS-OLL. The order of the filters are chosen as 36 for all the filter to have an efficient response and filtering.

TABLE I
Optimized Coefficients of FIR-LPF

h(N)	PSO	HS-OL	DRHS-OLL
h(1), h(37)	-0.00519	0.00035	0
h(2), h(36)	-0.01936	-0.00751	0.00163
h(3), h(35)	-0.02741	-0.02376	0
h(4), h(34)	-0.01218	-0.02711	-0.003
h(5), h(33)	0.01391	-0.00275	0
h(6), h(32)	0.01365	0.01911	0.00597
h(7), h(31)	-0.01296	0.00272	0
h(8), h(30)	-0.01798	-0.02201	-0.01106
h(9), h(29)	0.01401	-0.00273	0
h(10), h(28)	0.02539	0.02879	0.01907
h(11), h(27)	-0.01526	0.003	0
h(12), h(26)	-0.03715	-0.03992	-0.03167
h(13), h(25)	0.01643	-0.00336	0
h(14), h(24)	0.05745	0.05949	0.05313
h(15), h(23)	-0.0173	0.00367	0
h(16), h(22)	-0.10227	-0.10352	-0.09944
h(17), h(21)	0.01785	-0.00389	0
h(18), h(20)	0.31701	0.31744	0.31568
h(19)	0.48197	0.50397	0.49936

B. HPF

The magnitude response of the HPF is shown in Fig. 2a and the magnified pass band and stop band are shown in Fig. 2b and 2c respectively. The normalized cut-off frequency is chosen as 0.5 and the optimal order of the FIR filter is found to be 36 for more efficient filtering. Fig. 2d shows the linear phase response of the FIR filters with optimized coefficients using various optimization algorithms.

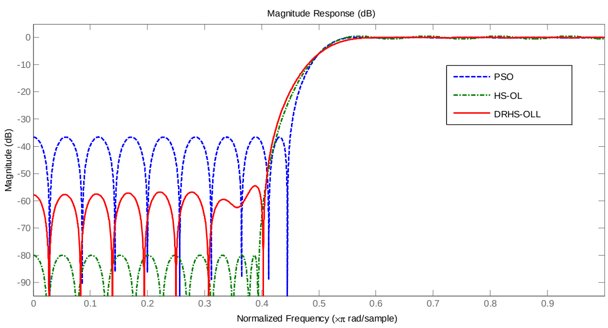

Fig. 2a: magnitude response of HPF

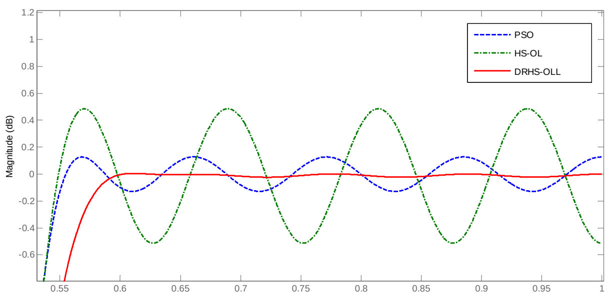

Fig. 2b: Magnified view of passband in magnitude response of HPF

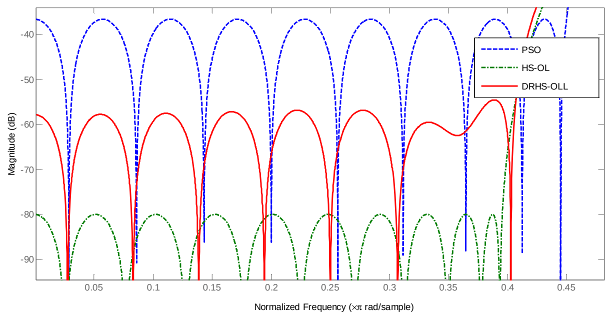

Fig. 2c: Magnified view of stopband in magnitude response of HPF

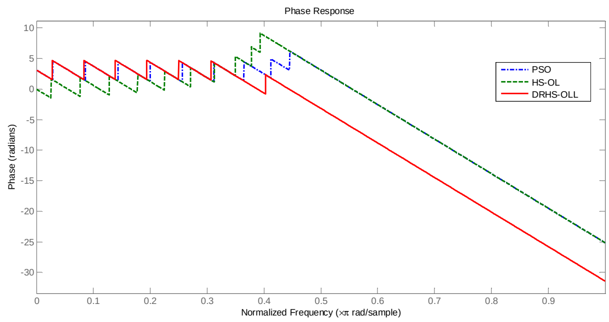

Fig. 2d: Phase response of HPF

The Table II lists the High Pass FIR filter coefficients of the three optimization techniques namely PSO, HS-OL and DRHS-OLL. The order of the filters are chosen as 36 for all the filter to have an efficient response and filtering.

TABLE II
Optimized Coefficients of FIR-HPF

h(N)	PSO	HS-OL	DRHS-OLL
h(1), h(37)	0.00E+00	-7.10E-04	-7.10E-04
h(2), h(36)	-1.13E-02	5.57E-03	5.57E-03
h(3), h(35)	0.00E+00	-1.43E-02	-1.43E-02
h(4), h(34)	9.56E-03	1.52E-02	1.52E-02
h(5), h(33)	0.00E+00	5.90E-04	5.90E-04
h(6), h(32)	-1.37E-02	-1.38E-02	-1.38E-02
h(7), h(31)	0.00E+00	4.80E-04	4.80E-04
h(8), h(30)	1.93E-02	1.78E-02	1.78E-02
h(9), h(29)	0.00E+00	-1.07E-03	-1.07E-03
h(10), h(28)	-2.71E-02	-2.52E-02	-2.52E-02
h(11), h(27)	0.00E+00	1.77E-03	1.77E-03
h(12), h(26)	3.88E-02	3.69E-02	3.69E-02
h(13), h(25)	0.00E+00	-2.48E-03	-2.48E-03
h(14), h(24)	-5.88E-02	-5.72E-02	-5.72E-02
h(15), h(23)	0.00E+00	3.09E-03	3.09E-03
h(16), h(22)	1.03E-01	1.02E-01	1.02E-01
h(17), h(21)	0.00E+00	-3.50E-03	-3.50E-03
h(18), h(20)	-3.17E-01	-3.17E-01	-3.17E-01
h(19)	5.00E-01	5.04E-01	5.04E-01

C. BPF

The magnitude response of the BPF is shown in Fig. 3a and the magnified pass band and stop band are shown in Fig. 3b and 3c respectively. The normalized cut-off frequency is chosen as 0.2 to 0.7 and the optimal order of the FIR filter is found to be 36 for more efficient filtering.

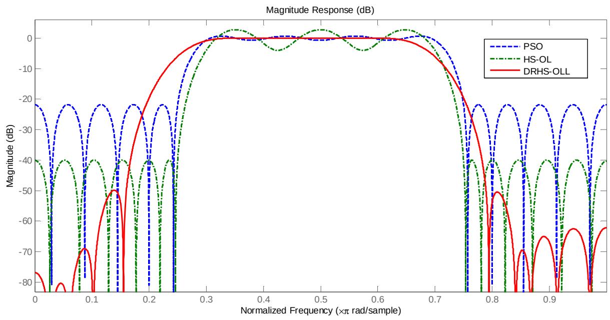

Fig. 3a: Magnitude response of BPF

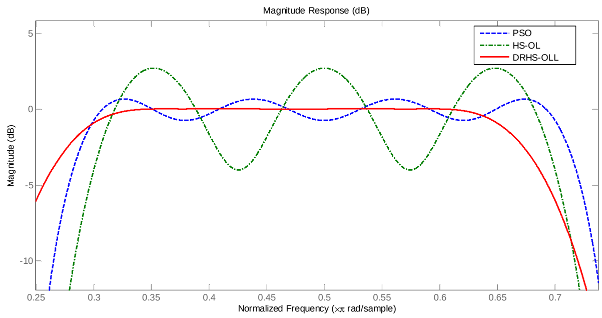

Fig. 3b: Magnified view of passband in magnitude response of BPF

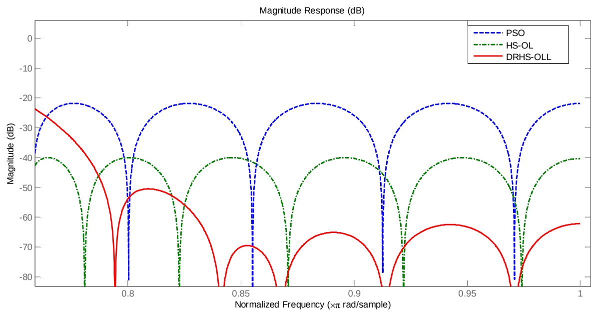

Fig. 3c: Magnified view of stopband in magnitude response of BPF

The Table III lists the Band pass FIR filter coefficients of the three optimization techniques namely PSO, HS-OL and DRHS-OLL. The order of the filters are chosen as 36 for all the filter to have an efficient response and filtering.

TABLE III
Optimized Coefficients of FIR-BPF

h(N)	PSO	HS-OL	DRHS-OLL
h(1), h(37)	-8.24E-03	5.62E-03	-7.00E-05
h(2), h(36)	0.00E+00	2.00E-05	-1.66E-03
h(3), h(35)	-5.64E-02	2.11E-02	-1.26E-03
h(4), h(34)	0.00E+00	-2.00E-05	5.15E-03
h(5), h(33)	2.08E-02	-7.52E-02	1.76E-03
h(6), h(32)	0.00E+00	5.00E-05	2.39E-03
h(7), h(31)	3.62E-02	1.05E-01	7.84E-03
h(8), h(30)	0.00E+00	-5.00E-05	-1.68E-02
h(9), h(29)	-4.04E-02	-4.83E-02	-1.47E-02
h(10), h(28)	0.00E+00	5.00E-05	1.95E-03
h(11), h(27)	-4.36E-02	-6.31E-02	-2.35E-02
h(12), h(26)	0.00E+00	-2.00E-05	3.23E-02
h(13), h(25)	9.10E-02	9.04E-02	6.50E-02
h(14), h(24)	0.00E+00	1.00E-05	-1.56E-02
h(15), h(23)	4.83E-02	6.47E-02	4.19E-02
h(16), h(22)	0.00E+00	1.00E-05	-3.98E-02
h(17), h(21)	-3.13E-01	-3.12E-01	-3.03E-01
h(18), h(20)	0.00E+00	0.00E+00	3.23E-02
h(19)	4.50E-01	4.34E-01	4.51E-01

D. BSF

The magnitude response of the BSF is shown in Fig. 4a and the magnified pass band and stop band are shown in Fig. 4b and 4c respectively. The normalized cut-off frequency is chosen as 0.2 to 0.75 and the optimal order of the FIR filter is found to be 36 for more efficient filtering.

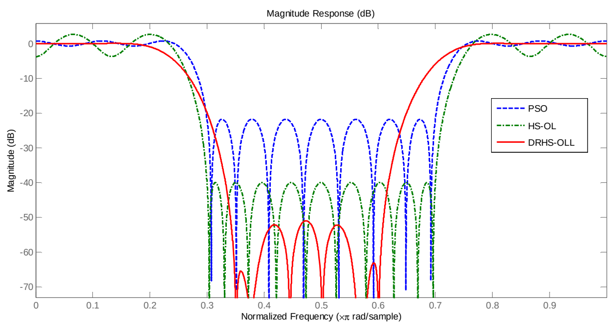

Fig. 4a: magnitude response of BSF

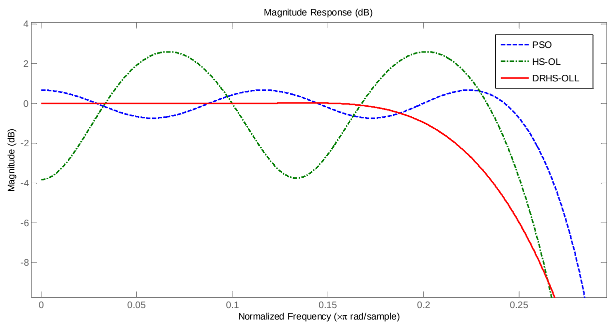

Fig. 4b: Magnified view of passband in magnitude response of BSF

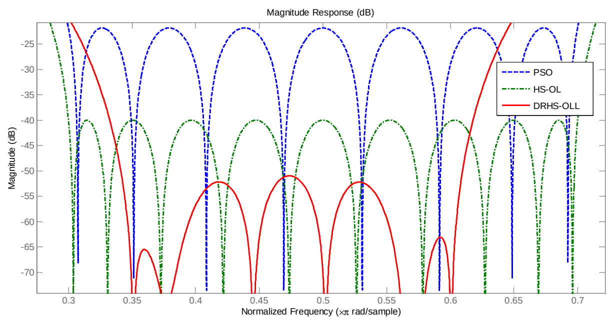

Fig. 4c: Magnified view of stopband in magnitude response of BSF

The Table IV lists the Band stop FIR filter coefficients of the three optimization techniques namely PSO, HS-OL and DRHS-OLL. The order of the filters are chosen as 36 for all the filter to have an efficient response and filtering.

TABLE IV
Optimized Coefficients of FIR-BSF

h(N)	PSO	HS-OL	DRHS-OLL
h(1), h(37)	8.24E-03	-5.51E-03	7.00E-05
h(2), h(36)	0.00E+00	-2.00E-05	1.66E-03
h(3), h(35)	5.64E-02	-6.13E-02	1.26E-03
h(4), h(34)	0.00E+00	-6.00E-05	-5.13E-03
h(5), h(33)	-2.08E-02	-1.10E-01	-1.76E-03
h(6), h(32)	0.00E+00	-1.40E-04	-2.38E-03
h(7), h(31)	-3.62E-02	-4.87E-02	-7.82E-03
h(8), h(30)	0.00E+00	-1.90E-04	1.68E-02
h(9), h(29)	4.04E-02	6.61E-02	1.47E-02
h(10), h(28)	0.00E+00	-1.90E-04	-1.95E-03
h(11), h(27)	4.36E-02	3.66E-02	2.35E-02
h(12), h(26)	0.00E+00	-1.60E-04	-3.22E-02
h(13), h(25)	-9.10E-02	-1.04E-01	-6.49E-02
h(14), h(24)	0.00E+00	-1.60E-04	1.56E-02
h(15), h(23)	-4.83E-02	-3.41E-02	-4.18E-02
h(16), h(22)	0.00E+00	-2.00E-04	3.96E-02
h(17), h(21)	3.13E-01	3.17E-01	3.02E-01
h(18), h(20)	0.00E+00	-2.50E-04	-3.22E-02
h(19)	5.50E-01	5.33E-01	5.50E-01

V. Parameter Selection

To compare the robustness and efficiency of the optimization algorithms, the parameters as described in the literature are taken and the HS-OL and DRHS-OLL shares all the common parameters.

- For PSO, Population size = 120, iteration cycles = 600, $C1$ =$C2$ =2.05, V_i^{min}= 0.01, V_i^{max} =1.0, w_{max}= 1.0, and w_{min}= 0.4.
- For HS-OL, Population size = 120; iteration cycles = 600; HMCR= 0.6, PAR_{min}=0; PAR_{max}= 0.9; BW_{min}= 0.000001; and BW_{max}=1.
- For DRHS-OLL, Population size = 120; iteration cycles = 600; HMCR= 0.6, PARmin=0; PARmax= 0.9;BW_{min}= 0.000001; and BW_{max}=1, No. of groups, GP= 10, Initial group sizes, GPS_i= 5 (i= 1,…,10) and the regrouping period, refreshGap= 10.

VI. Results and discussion

The Table V clearly shows the average pass band ripple of the FIR filters optimized by the three optimization algorithms namely PSO, HS-OL and DRHS-OLL. The pass band ripple is very low for the proposed DRHS-OLL based FIR optimization technique and it shows almost flat response in the pass band. Also from the Table VI, it is clear that the stop-band ripple of the DRHS-OLL algorithms is more for LPF and HPF, but it is in the acceptable range and hence the response of the filter is still improved as it has the least pass-band ripple. The stop band ripple of the BPF and BSF is very high compared to the other optimization methods.

TABLE V
Comparison of Average Pass Band Ripple (dB) of Optimized FIR filter

Optimization Algorithm	Filter Type			
	LPF	HPF	BPF	BSF
PSO	1.33	0.14	0.32	0.43
HS-OL	1.23	0.28	1.38	2.38
DRHS-OLL	0.03	0.007	0.002	0.004

TABLE VI
Comparison of Average Stop Band Ripple (dB) of Optimized FIR filter

Optimization Algorithm	Filter Type			
	LPF	HPF	BPF	BSF
PSO	-62.26	-40.21	-23.21	-26.43
HS-OL	-63.11	-82.65	-42.73	-42.28
DRHS-OLL	-59.93	-61.32	-68.45	-60.23

VII. Conclusions and Future work

An FIR filter optimization techniques is presentes and it adapts the DRHS-OLL algorithm to optimize the FIR filter coefficients for all the four types viz. LPF, HPF, BPF and BSF. The magnitude response of the FIR filters with optimized filter coefficients using DRHS-OLL show promising results. The DRHS-OLL based algorithm certainly performs better compared to the conventional HS optimization algorithm in terms of premature convergence and stagnation. Random regrouping and independent HS of each group along with opposition based harmony creation and periodic local search yields better results for the FIR filter design problem.

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