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Teaching Learning Based Optimization Algorithm for the Optimal Design of Higher Order BP and BS IIR Digital Filter

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Abstract

Digital filter is an integral component of digital signal processing system. Digital infinite impulse response (IIR) filter has the advantages of high selectivity and less computation cost as compared to finite impulse response (FIR) filter. In this paper Teaching-Learning opposition based optimization (TLOBO) algorithm is applied to design the optimal higher order band pass (BP) and band stop (BS) IIR filter in terms of magnitude response. The original Teaching- Learning Based Optimization (TLBO) algorithm has been retailored by blending the concept of opposition-based learning for selection of good candidates. TLOBO does not require the determination of any algorithm specific controlling parameters which makes the algorithm robust and powerful. The computational experiments show that the proposed TLOBO is superior to other heuristic algorithms and can be efficiently used for digital IIR filter design.

Keywords: Digital IIR filter; Magnitude response; Stability; Teaching-Learning Based Optimization (TLBO); passband and stopband ripples.

1. Introduction

The advantages of digital filter over analog filter are flexibility, repeatability, remote processing, power consumption and size. Digital filters play a crucial role in almost every application of digital signal processing like image processing, video processing, digital communication, biomedical and radar processing. Digital filters are used to modify the frequency spectrum of the discrete signal to get output according to some desired specifications. Digital infinite impulse response (IIR) filter is computationally efficient as compared to finite impulse response (FIR) filter [1, 2]. The error surface of IIR filter is non-linear and multimodal in nature due to the presence of denominator coefficients in the transfer function. The conventional gradient based algorithms get easily stuck in the local minima. Hence efficient optimization algorithms are required in order to search global minima of multimodal error surface of IIR digital filters [3]. In the recent years, various heuristic optimization methods have been proposed for the design of IIR digital filters such as: genetic algorithms [4-8], ant colony optimization [9], immune algorithm [10], heuristic search method [11], Seeker optimization algorithm [12], particle swarm optimization [13, 14], two-stage ensemble evolutionary algorithm [15], gravitation search algorithm [16] and many more.

All heuristic and swarm intelligence based algorithms use probabilistic processes to generate new (potential) solutions to a problem and require algorithm specific control parameters in addition to common controlling parameters like population size, number of generations, elite size**,** etc. To overcome all these obstacles, Teaching-learning based optimization (TLBO) algorithm inspired by teaching-learning process has been proposed by Rao et al. [17, 18]. The implementation of TLBO does not require determination of any algorithm specific controlling parameters which makes the algorithm robust and powerful. TLBO requires only common controlling parameters like population size and number of generations for its working.

In this paper the exploration capability of TLBO is further intensified by incorporating the concept of opposition-based learning for initializing with good learners. The performance of Teaching-learning opposition based optimization (TLOBO) algorithm is investigated for the design of higher order bandpass (BP) and bandstop (BS) IIR filters in terms of magnitude approximation while employing the stability constraints. The filter coefficients are optimized to achieve the minimum magnitude response error in terms of L_p -approximation error criterion. The results of the designed filter are compared with hierarchical genetic algorithm (HGA) [7], hybrid taguchi genetic algorithm (HTGA) [8] and taguchi immune algorithm (TIA) [10] to show the effectiveness of TLOBO algorithm.

The paper is structured as follows. IIR filter design problem is described in Section 2. The TLOBO algorithm for designing the 8th order BP and 6th order BS digital IIR filters is described in Section 3. In Section 4, the achieved results are compared with the design obtained by [7], [8] and [10] for the BP and BS filters. Finally, the conclusions and discussions are described in Section 5.

2. Design Problem of IIR Filter

The design of IIR filter involves the searching of optimized value of the filter coefficient to meet the required design specification**.** The advantages of cascade structure are that overall transfer function of the filter can be determined and range of coefficients is limited. IIR digital filter can be expressed by the cascading first and second order sections [19] stated as:

$$H(\omega, X) = x_1 \cdot \prod_{l=1}^{u} \frac{1 + x_{2l} e^{-j\omega}}{1 + x_{2l+1} e^{-j\omega}} \times \prod_{m=1}^{v} \frac{1 + x_{4m+2u-2} e^{-j\omega} + x_{4m+2u-1} e^{-j2\omega}}{1 + x_{4m+2u} e^{-j\omega} + x_{4m+2u+1} e^{-j2\omega}} \quad (1)$$

X is a vector decision variable of dimension $S \times 1$ with $S = 2u + 4v + 1$. x_1 represents the gain, $[x_2, x_3, ..., x_{2u+4v+1}]$ denotes the filter coefficients of first and second order sections. Two design criterions to approximate the magnitude response of IIR filter are considered in this paper:

- Magnitude approximation employing L_1-error criterion
- Minimization of magnitude response L_1-error, L_2-error, ripples in passband and stopband simultaneously.

Ideal magnitude response $H_I(\omega_i)$ of IIR filter is given as:

$$H_I(\omega_i) = \begin{cases} 1, & for\ \ \omega_i \in passband \\ 0, & for\ \ \omega_i \in stopband \end{cases} \quad (2)$$

IIR filter should follow the following stability constraints for the filter to be stable:

$$1 + x_{2l+1} \geq 0 \ \ (l = 1, 2, ..., u) \quad (3a)$$

$$1 - x_{2l+1} \geq 0 \ \ (l = 1, 2, ..., u) \quad (3b)$$

$$1 - x_{4m+2u+1} \geq 0 \ (m = 1, 2, ..., v) \quad (3c)$$

$$1 + x_{4m+2u} + x_{4m+2u+1} \geq 0 \ (m = 1, 2, ..., v) \quad (3d)$$

$$1 - x_{4m+2u} + x_{4m+2u+1} \geq 0 \ (m = 1, 2, ..., v) \quad (3e)$$

The detail of design criterion employed to design digital IIR filters are presented in the next subsections.

2.1. L_1-approximation of magnitude response error

The magnitude response is specified at K equally spaced discrete frequency points in passband and stopband. In the first design criterion magnitude response error is minimized as the absolute error in terms of L_1-norm and is denoted as:

$$E_1(X) = \sum_{i=0}^{K} \left| H_I(\omega_i) - |H_d(\omega_i, X)| \right| \quad (4)$$

$E_1(X)$ denotes the absolute L_1-norm error of magnitude response. Accordingly the first objective to be optimized is defined as:

$$Minimize\, F(X) = E_1(X) \tag{5}$$

2.2 Multiobjective problem in terms of magnitude response, ripples in passband and stopband

In second design criterion: (i) magnitude response error as absolute error in terms of L_1-norm (ii) magnitude response error as squared error in terms L_2 -norm (iii) passband ripple magnitude and (iv) stopband ripple magnitude, are minimized simultaneously using weighted sum method.

L_2 -norm of magnitude response error is defined as given below:

$$E_2(X) = \sum_{i=0}^{K} \left(|H_I(\omega_i)| - |H_d(\omega_i, X)| \right)^2 \tag{6}$$

$E_2(X)$ denotes the squared error L_2-norm of magnitude response. The ripple magnitudes of passband and stopband denoted by $\delta_p(X)$ and $\delta_s(X)$ respectively are defined as:

$$\delta_p(X) = \max_{\omega_i} \left\{ |H_d(\omega_i, X)| \right\} - \min_{\omega_i} \left\{ |H_d(\omega_i, X)| \right\} \quad for\, \omega_i \in passband \tag{7}$$

and

$$\delta_s(X) = \max_{\omega_i} \left\{ |H_d(\omega_i, X)| \right\} \quad for\, \omega_i \in stopband \tag{8}$$

Aggregating all objectives, the multiobjective constrained optimization problem consisting of multiple objectives is stated as:

$$\begin{aligned} &\text{Minimize} \quad j_1(X) = E_1(X) \\ &\text{Minimize} \quad j_2(X) = E_2(X) \\ &\text{Minimize} \quad j_3(X) = \delta_p(X) \\ &\text{Minimize} \quad j_4(X) = \delta_s(X) \end{aligned} \tag{9}$$

Multiple objectives as defined above are optimized simultaneously by combining them into a single objective by assigning different weights to each of them.

There will be multiple optimal solutions depending on the value of different weights. In this paper weights are taken same as given by Tsai and Chou [10]. The function to be optimized is defined as:

$$\text{Minimize} \quad F(X) = \sum_{p=1}^{4} w_p j_p(X) \tag{10}$$

Subject to: The stability constraints given by Eq. (3a) to Eq. (3e), where w_p is non-negative real number called weight.

The design of causal recursive filters requires the inclusion of stability constraints. Therefore, the stability constraints which are obtained by using the Jury method [20] on the coefficients of the digital IIR filter in Eq. (2) have been forced to satisfy by updating the coefficients with random variation [21].

3. TLOBO Algorithm

The stepwise procedure followed for the design of IIR digital filter applying TLOBO is presented in this section. The motivation of TLOBO comes from a social precedence of learner acquiring knowledge from their teachers. TLOBO is a population based global optimization technique which explores a population of solutions to proceed to the global solution. The learners are analogous to population and filter coefficients constitute the members of the population in TLOBO.

The decision variables of the IIR filter design problem are coefficients of the filter, hence there are used to form the class. The set of filter coefficients (X_i) is represented as the subjects assigned to learners in a class. For a filter with S coefficients, the learner is represented as a vector of length S. The i^{th} learner is represented as $X_i = [x_{i1}, x_{i2,...,} x_{iS}]$. If there are NL learners in a class, the complete class is represented as a matrix shown below:

$$class = \begin{bmatrix} X_{11} & X_{12} & .. & .. & X_{1S} \\ X_{21} & X_{22} & .. & .. & X_{2S} \\ . & . & X_{ij} & .. & . \\ . & . & .. & .. & . \\ X_{NL1} & X_{NL2} & .. & .. & X_{NLS} \end{bmatrix} \begin{matrix} \to f(X_1) \\ \to f(X_2) \\ \to f(X_i) \\ .. \\ \to f(X_{NL}) \end{matrix}$$

where x_{ij} is the j^{th} subject score of i^{th} learner and $f(X_i)$ represent the objective function.

The search process is started by initializing the learners by performing a random search:

$$X_j = X_j^{\min} + (X_j^{\max} - X_j^{\min}) \cdot R() \quad (j = 1, 2, \ldots, S) \tag{11}$$

where R is a uniform random generated number between (0,1), S is number of subjects allotted to each learner, $X_j^{\max}$ and $X_j^{\min}$ are the maximum and minimum values of j^{th} decision variable (filter coefficient) of vector X.

The expected fitness function f of i^{th} learner of class is given below:

$$f(X_i) = \text{Minimize } (F_i(X)) \quad (i = 1,2,\ldots,NL) \qquad (12)$$

where F_i *(X)* for i^{th} learner of class is obtained using Eq. (5) or Eq. (10) depending upon the design criteria applied.

The working of TLOBO is broadly classified into two phases: Teacher phase and Learner phase. A teacher act as a mentor and disseminate knowledge among the learners, and helps them to get good grades. The learners in addition to gaining knowledge from their teacher, also learn from interaction among themselves.

3.1. Opposition-based learning

The concept of opposition-based learning [22] is applied to accelerate the converge rate of TLOBO. The current population and its opposite population (X_j^{op}) is considered at the same time in order to select better current candidate solution.

$$X_j^{op} = X_j^{\max} - R()(X_j^{\max} - X_j^{\min}) \quad (j = 1,2,\ldots,S) \qquad (13)$$

The best *NL* learners are selected out of the opposite population (X_j^{op}) generated using Eq. (13) and initial *NL* learners generated using Eq. (11) to initialize a class.

Further the opposition-based learning is also employed for generating new learners after the completion of learner phase using:

$$X_j^{op} = X_j^U + X_j^L - X_j \quad (j = 1,2,\ldots,S) \qquad (14)$$

where

$$X_j^U = \max\{X_j;\ (j = 1,2,\ldots,S)\} \text{ and } X_j^L = \min\{X_j;\ (j = 1,2,\ldots,S)\}$$

3.2. Teacher phase

The learners of a class are evaluated as if the examination is conducted. The learner with best fitness function value is designated as the teacher. The teacher puts best of his effort to raise the mean score of the learners near to his own level. In teacher phase a random process is followed in which for each learner or position a new position is generated given by:

$$X_{new}^S = X_{old}^s + R() \times (X_{teach}^S - T_f Mean_s) \qquad (15)$$

X_{old}^s is the old position of learner i.e. he still has to acquire knowledge from the teacher. The position of learner is represented by a vector of length (*1* × *S*) representing his outcome for each subject or course, *R()* is a random number in the range [0,1], X_{teach}^{S} is the best learner in this iteration who will try to change the mean of the class toward his position, T_f is a teaching factor, and $Mean_s$ is a vector of dimension ($1 \times S$) representing the mean or average values of the class outcomes for each particular subject or course. The value of T_f decides about the volume of effect a teacher has on the output of a learner. In this paper the value of T_f is randomly selected as 1 or 2. The new learner X_{new}^{s} is accepted if he is better in terms of function value than the old learner.

3.3. Learner phase

The learners enhance their knowledge base in two steps: (i) learning from teacher (ii) sharing the knowledge among themselves i.e. through tutorials, seminars etc. This learner phase emulates the second phase of mutual interaction. Two target learners namely i and k are selected randomly such that i ≠ k. The resultant new learners after sharing / exchange of know-how are generated as follows:

$$X_{new,\,i}^{j} = \begin{cases} X_{old,\,i}^{j} + R(\,)\times(X_{old,\,i}^{j} - X_{k}^{j}) & ; f(X_i) < f(X_k) \\ X_{old,\,i}^{j} + R(\,)\times(X_{k}^{j} - X_{old,\,i}^{j}) & ;Otherwise \end{cases} \qquad (j = 1,2,\ldots,S) \quad (16)$$

The individual $X_{new,i}$ is accepted if he is better than the old individual $X_{old,i}$.

3.4. Stopping criteria

At the end of the learning phase, a cycle (iteration) is completed. Initially at the end of first iteration, the function value of the fittest learner is set as global best (f^{best}) and corresponding marks scored by him in various subjects are set as global best marks (B_j). At end of each subsequent iterations if the function value obtained by the best learner is better than the global best (f^{best}) then it replaces the global best and corresponding marks obtained by the best learner are stored as the global best marks (B_j). This process is continued until a stopping criterion of predetermined maximum iterations is met.

4. Simulation Results and Comparisons

TLOBO is applied to design 6th order BP and 4th order BS IIR filters using two different design criterions for the magnitude approximation in frequency domain. The obtained results are compared to the performance of designed IIR filter of [7], [8] and [10]. In the BP filter designing, the prescribed range of passband and stopband are taken as $0.4\pi \le w \le 0.6\pi$ and $0 \le w \le 0.25\pi$, $0.75\pi \le w \le \pi$ respectively. In the BS filter designing, the prescribed range of passband and stopband are taken as $0 \le w \le 0.25\pi$, $0.75\pi \le w \le \pi$ and $0.4\pi \le w \le 0.6\pi$, respectively. For designing digital IIR filter 200 equally spaced points are set within the frequency domain [0, π].

The magnitude response approximation as absolute error in terms of L_1-norm error criterion is considered as first design criteria. The computational results obtained by the proposed TLOBO approach are presented and compared with the results obtained by [7], [8] and [10] in Table 1 and Table 2. The obtained magnitude response is presented in Figure 1 for the designed BP and BS filters. For the designed IIR filter to be stable and have minimum phase, all the poles and zeros of designed filters should lie inside the unit circle. Figure 2 shows the pole-zero plots of designed 8th order BP and 6th order BS IIR filters respectively. It is observed from Figure 2 that maximum radii of poles are 0.8833 and 0.8390 for BP and BS filters, respectively. The best optimized 8th order numerator coefficients and denominator coefficients obtained by the TLOBO approach for 8th order BP and 6th BS are given by Eq. (17) and Eq. (18) respectively.

$$H_{BP}(z) = 0.021666 \left(\frac{(z^2 - 0.02269\ z - 0.68541)}{(z^2 - 0.00201\ z + 0.38351)}\right) \times \left(\frac{(z^2 - 0.00049\ z - 0.69959)}{(z^2 - 0.65332\ z + 0.780162)}\right) \times \left(\frac{(z^2 + 0.000715\ z - 0.70174)}{(z^2 + 0.648415\ z + 0.779839)}\right) \times \left(\frac{(z^2 - 0.03892\ z - 0.68541)}{(z^2 - 0.00372\ z + 0.390065)}\right) \tag{17}$$

$$H_{BS}(z) = 0.25996 \left(\frac{(z^2 + 0.506822\ z + 0.959396)}{(z^2 + 0.160982\ z + 0.099999)}\right) \times \left(\frac{(z^2 - 0.39512\ z + 1.004351)}{(z^2 - 0.90325\ z + 0.609891)}\right) \times \left(\frac{(z^2 + 0.315163\ z + 1.044604)}{(z^2 + 1.042933\ z + 0.703971)}\right) \tag{18}$$

Table 1. Design results for 8th order BP using L_1-error criterion

Method	**Order**	**L_1-norm error**	**Pass-band performance (Ripple magnitude)**	**Stop-band performance (Ripple magnitude)**
TLOBO	8	0.7119	$0.9887 \le \lvert H(e^{j\omega}) \rvert \le 1.006$ (0.0180)	$\lvert H(e^{j\omega}) \rvert \le 0.0344$ (0.0344)
HGA [5]	6	5.2165	$0.8956 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.1044)	$\lvert H(e^{j\omega}) \rvert \le 0.1772$ (0.1772)
HTGA [8]	6	1.5367	$0.9677 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0323)	$\lvert H(e^{j\omega}) \rvert \le 0.0680$ (0.0680)
TIA [10]	6	1.5204	$0.9681 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0319)	$\lvert H(e^{j\omega}) \rvert \le 0.1638$ (0.0679)

Table 2. Design results for 6th order BS filter using L_1-error criterion

Method	**Order**	**L_1-norm error**	**Pass-band performance (Ripple magnitude)**	**Stop-band performance (Ripple magnitude)**
TLOBO	6	1.0467	$0.9543 \le \lvert H(e^{j\omega}) \rvert \le 1.004$ (0.0501)	$\lvert H(e^{j\omega}) \rvert \le 0.0707$ (0.0707)
HGA [5]	4	6.6072	$0.8920 \le \lvert H(e^{j\omega}) \rvert \le 1.009$ (0.1080)	$\lvert H(e^{j\omega}) \rvert \le 0.1726$ (0.1726)
HTGA [8]	4	3.6334	$0.9425 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0575)	$\lvert H(e^{j\omega}) \rvert \le 0.1294$ (0.1294)
TIA [10]	4	3.4750	$0.9259 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0741)	$\lvert H(e^{j\omega}) \rvert \le 0.1278$ (0.1278)

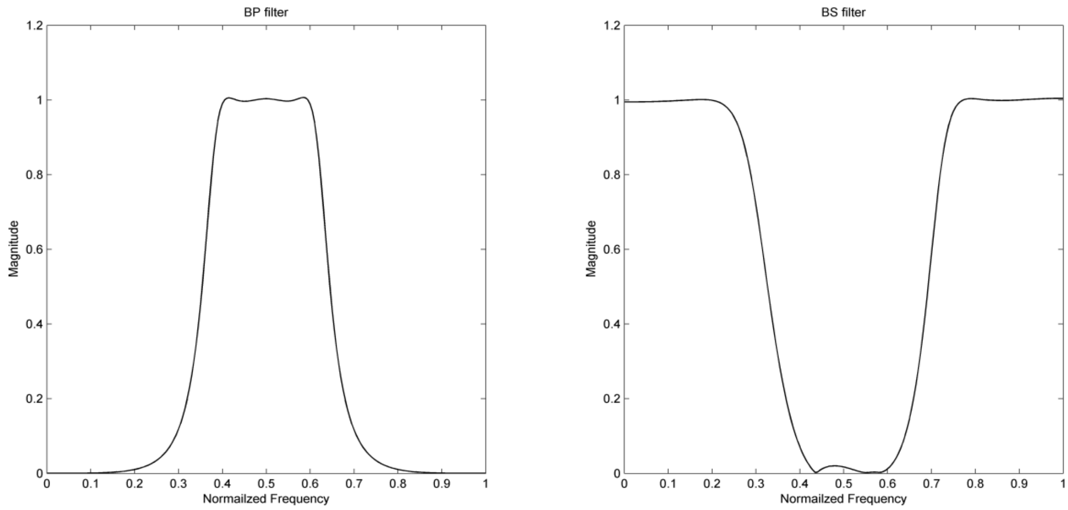

Figure 1. Magnitude response of 8th order BP and 6th order BS IIR filter using L_1-error criterion

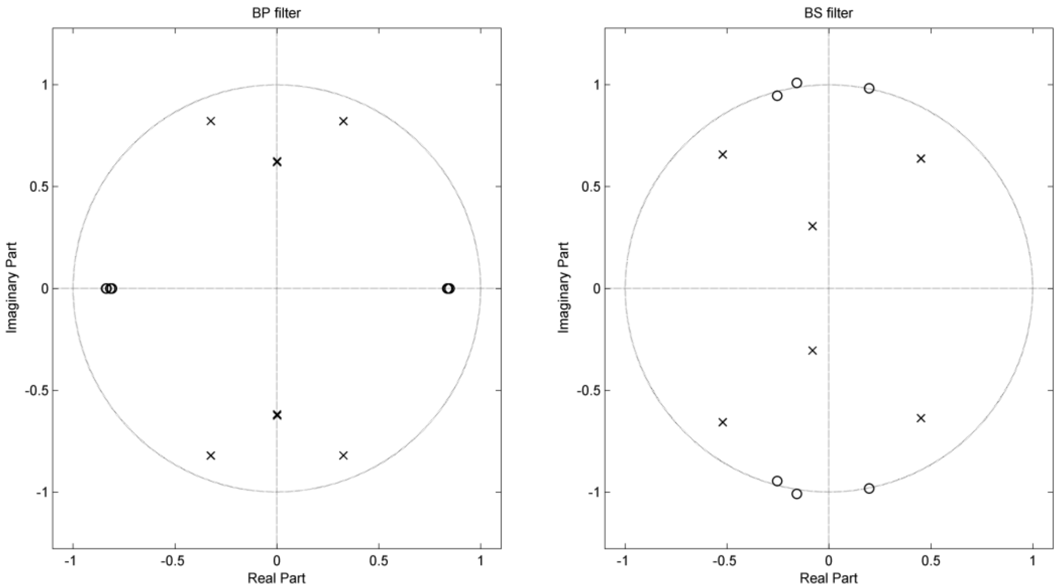

Figure 2: Pole-Zero plot of 8th order BP and 6th order BS IIR filter employing L_1-error criterion

In second design criterion the combination of four criteria, absolute error as L_1-norm approximation error of magnitude response, squared error as L_2-norm approximation of magnitude response, ripple magnitudes of pass-band and ripple magnitude of stop-band are considered simultaneously. TLOBO approach employing weighted sum method is applied to minimize the objective function given by Eq. (10) under the prescribed design conditions. The four criteria are contrary to each other in most situations. The filter designer needs to adjust the weights of different objectives to design the filter depending on the filter specifications. For the purpose of comparison the weights w_1, w_2, w_3 *and* w_4 are set to be same as in [10] for the BP and BS filters respectively.

The computational results obtained by the proposed TLOBO approach are presented and compared with the results obtained by [7], [8] and [10] in Tables 3 and Table 4. Magnitude response is presented in Figure 3 for the designed 8th order BP and 6th order BS IIR digital filters respectively. Figure 4 shows the pole-zero plot of 8th order BP and 6th order BS IIR filters respectively designed with TLOBO. It is observed from Figure 4 that maximum radii of poles are 0.8814 and 0.8656 for BP and BS filters, respectively. The best optimized numerator coefficients and denominator coefficients obtained by the TLOBO approach for 8th order BP and 6th order BS filter are given by Eq. (19), Eq. (20), respectively.

$$H_{BP}(z) = 0.010119 \left(\frac{(z^2 - 0.02612\ z - 1.44748\ )}{(z^2 - 0.00091\ z + 0.369945\ )}\right) \times \left(\frac{(z^2 - 0.00026\ z - 1.06816\ )}{(z^2 - 0.67409\ z + 0.776195\ )}\right)$$
$$\times \left(\frac{(z^2 + 0.001101\ z - 1.16846\ )}{(z^2 + 0.67028\ z + 0.776951\ )}\right) \times \left(\frac{(z^2 - 0.04101\ z - 0.77565\ )}{(z^2 - 0.00488\ z + 0.377115\ )}\right) \quad (19)$$

$$H_{BS}(z) = 0.317211 \left(\frac{(z^2 + 0.427552\ z + 0.970309\ )}{(z^2 + 0.157823\ z + 0.142506\ )}\right) \times \left(\frac{(z^2 - 0.51979\ z + 0.981851\ )}{(z^2 - 0.88543\ z + 0.652617\ )}\right) \times \left(\frac{(z^2 + 0.41286\ z + 1.017333\ )}{(z^2 + 0.967294\ z + 0.749216\ )}\right) \quad (20)$$

Table 3. Design results for 8th order BP filter employing minimization of $E_1(X) + E_2(X) + \delta_p(X) + \delta_s(X)$

Method	**Order**	***L_1*-norm error**	***L_2*-norm error**	**Pass-band performance (Ripple magnitude)**	**Stop-band performance (Ripple magnitude)**
TLOBO	8	0.7599	0.1174	$0.9931 \le \lvert H(e^{j\omega}) \rvert \le 1.001$ (0.0087)	$\lvert H(e^{j\omega}) \rvert \le 0.0383$ (0.0383)
HGA [5]	6	5.2165	0.6949	$0.8956 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.1044)	$\lvert H(e^{j\omega}) \rvert \le 0.1772$ (0.1772)
HTGA [8]	6	1.9418	0.2350	$0.9760 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0234)	$\lvert H(e^{j\omega}) \rvert \le 0.0711$ (0.0711)
TIA [10]	6	1.6119	0.2191	$0.9806 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0194)	$\lvert H(e^{j\omega}) \rvert \le 0.0658$ (0.0658)

Table 4. Design results for 6th order BS filter employing minimization of $E_1(X) + E_2(X) + \delta_p(X) + \delta_s(X)$

Method	**Order**	***L_1*-norm error**	***L_2*-norm error**	**Pass-band performance (Ripple magnitude)**	**Stop-band performance (Ripple magnitude)**
TLOBO	6	1.3637	0.1895	$0.9910 \le \lvert H(e^{j\omega}) \rvert \le 1.006$ (0.0154)	$\lvert H(e^{j\omega}) \rvert \le 0.0470$ (0.0470)
HGA [5]	4	6.6072	0.7903	$0.8920 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.1080)	$\lvert H(e^{j\omega}) \rvert \le 0.1726$ (0.1726)
HTGA [8]	4	4.5504	0.4824	$0.9563 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0437)	$\lvert H(e^{j\omega}) \rvert \le 0.1013$ (0.1013)
TIA [10]	4	4.1275	0.4752	$0.9560 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0440)	$\lvert H(e^{j\omega}) \rvert \le 0.1164$ (0.1164)

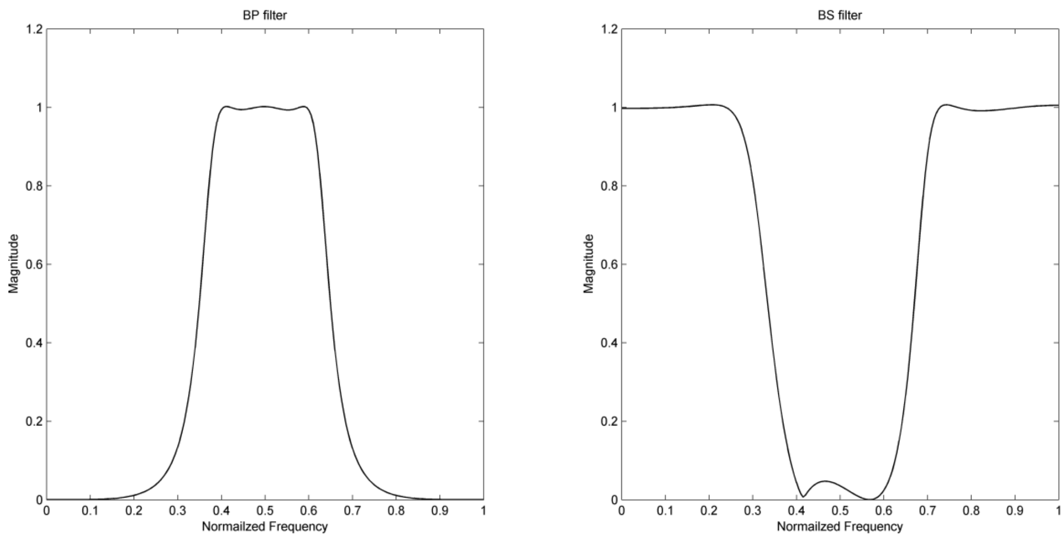

Figure 3. Magnitude response of 8th order BP and 6th order BS IIR filter employing $E_1(X)+E_2(X)+\delta_p(X)+\delta_s(X)$ **criterion.**

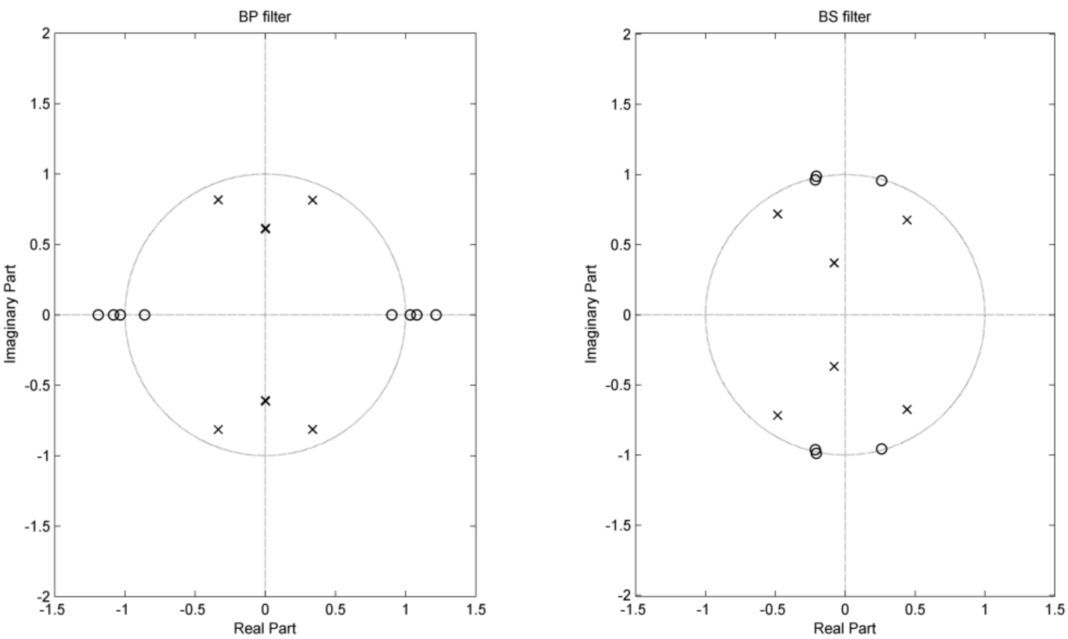

Figure 4. Pole-Zero of 8th order BP and 6th order BS IIR filter employing $E_1(X)+E_2(X)+\delta_p(X)+\delta_s(X)$ **criterion**

The critical analysis of the obtained results that the designed IIR digital filters employing TLOBO show significant reduction in magnitude response L_1 –error, L_2-error and magnitude of ripples in passband and stopband in comparison to filter design given by [7], [8] and [10]. On the contrary the point of concern is that the order of the IIR filters obtained employing TLOBO is higher in comparison to filter design given by [7], [8] and [10] which can subsequently lead to increase in quantization error. The increase in quantization error can ultimately make the designed filter unstable. In order to check for the stability of designed filters the Pole-Zero diagrams of designed IIR filters with TLOBO are obtained and are depicted in Figure 2 and Figure 4. The designed filters with TLOBO are stable, as all poles lie inside the unit circle. The zeroes lying outside the unit circle does not affect the stability of the filter. Last but not least TLOBO algorithm requires to tune only the common control parameters and not the algorithm-specific parameters. In view of above discussion it is concluded that TLOBO is a robust and effective algorithm for the design of digital IIR filters of better responses.

5. Conclusion

The proposed TLOBO algorithm strives to minimize magnitude response error and ripples in passband and stopband of BP and BS digital IIR filters. The main advantage of the TLOBO algorithm is that it requires to tune common control parameters and not the algorithm-specific parameters. TLOBO obtain global solutions with less computational effort and high consistency. On the basis of results obtained for the design of BP and BS digital IIR filters, it can be concluded that the proposed method is efficient algorithm with higher optimizing accuracy and strong global search ability as compared to other heuristic optimization methods.

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