Design of Higher Order LP and HP Digital IIR Filter Using the Concept of Teaching-Learning Based Optimization

DAMANPREET SINGH[1], J.S. DHILLON[2]
Department of Computer Science & Engineering[1]
Department of Electrical & Instrumentation Engineering[2]
Sant Longowal Institute of Engineering and Technology, Longowal[1,2]
INDIA[1,2]
damanpreetsingh@sliet.ac.in[1], jsdhillon@sliet.ac.in[2]

Abstract: – In this article, Teaching-learning opposition based optimization (TLOBO) algorithm based on the natural phenomenon of teaching and learning is applied to design an optimal higher order stable low pass (LP) and high pass (HP) IIR digital filter using different design criterion. The original Teaching- Learning Based Optimization (TLBO) algorithm has been remodeled by merging the concept of opposition-based learning for selection of good candidates. In the first part of design process absolute magnitude response error is minimized. In second design phase, combination of four criterion is considered i.e. L_1 -norm approximation of magnitude response, L_2-norm approximation of magnitude response, ripples in pass band and stop band are minimized simultaneously by applying multiobjective optimization. The obtained design results of LP and HP, IIR filter are compared to other existing meta-heuristic algorithms. The simulation results reveal that the purposed TLOBO algorithm gives better performance in terms of convergence rate and quality of the filter.

Key-Words:- Digital infinite impulse response filters; Teaching-Learning-Based Optimization (TLBO); Magnitude response; Filter ripples, Multiobjective optimization.

1. Introduction

Digital filter has a significant role in the field of digital signal processing. The main function of digital filter is to eliminate noise from the signal and to limit the bandwidth of the signals. Digital filters are broadly classified into two types based on the length of impulse response: finite impulse response (FIR) filter and infinite impulse response (IIR) filter [1]. As compared to FIR digital filter IIR digital filter requires lesser number of coefficients to get same frequency response. IIR digital filters are useful in a large range of applications where high selectivity and efficient processing of discrete signals are desirable [2]. The main problems associated with the designing of IIR digital filters are: Instability, non-linear phase response and multimodal error surface. Two types of techniques used to design IIR digital filters are transformation techniques and optimization techniques. The transformation approach for the design of digital IIR filters involves the transformation of an analog filter into digital filter using transformation techniques. Filter designed with transformation techniques are not efficient in terms of filter structure and coefficient quantization error. Gradient based classical algorithms [2-3] are fast but may stuck to local minima due to non-linear and multimodal error surface of IIR digital filter [2]. To overcome the shortfalls as described above and to obtain the global optimal solutions, various evolutionary algorithms applied for designing IIR digital are: genetic algorithm [4-8], ant colony optimization [9], immune algorithm [10], Seeker optimization algorithm [11], particle swarm optimization [12-13], two-stage ensemble evolutionary algorithm [14], gravitation search algorithm [15] and many more .

The execution of evolutionary algorithms requires the tuning of algorithm-specific control parameters in addition to fine-tuning of common controlling parameters such as population size, number of generations, elite size, etc. Teaching-learning based optimization (TLBO) algorithm proposed by Rao et al. [16-17] requires the fine-tuning of only common controlling parameters which makes it a robust and powerful global optimization algorithm.

The intent of this paper is to introduce enhancement in original TLBO to improve its exploration capabilities, by initializing with good candidates. The performance of Teaching-learning opposition based optimization (TLOBO) algorithm is investigated for designing higher order low pass (LP) and high pass (HP) IIR digital filter by employing two design criterions: (i) minimizing the magnitude response error using L_p-norm error criterion (ii) minimizing magnitude response error and ripples in pass band and stop band, simultaneously. The obtained results 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 arranged as follows. Section 2 describes the IIR filter design problem. The TLOBO algorithm for designing the optimal low-pass (LP) and high-pass (HP) 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 LP and HP filters. Finally, the conclusions and discussions are described in Section 5.

2. Design Problem of IIR Filter

Digital IIR filter design problem involves the determination of a set of filter coefficients which meet the following performance specifications:

- Magnitude approximation employ L_1-error criterion
- Minimization of magnitude response L_1-error, L_2-error, ripples in pass band and stop band simultaneously.

IIR digital filter can be expressed by the cascading first and second order sections [18] stated as:

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

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.

The IIR filter is designed by optimizing the coefficients such that the response of designed filter should be close to desired one.

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

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

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

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

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

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

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

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

In this paper two different design criterion are used to design the higher order LP and HP IIR digital filter and are described 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 pass band and stop band. In the first design criterion magnitude response error is minimized as the absolute error in terms of L_1-norm and is denoted as:

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

$E_1(X)$ denotes the absolute L_1-norm error of magnitude response. According to first design criterion, the 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 pass band and stop band

In second design criterion magnitude response error as absolute error in terms of L_1-norm, and as squared error in terms L_2 -norm, pass band and stop band 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 pass-band and stop-band are to be minimized, which are denoted by $\delta_p(X)$ and $\delta_s(X)$ respectively. Ripple magnitudes for pass band and stop band are defined as:

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

and

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

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

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

Multiple objectives as defined above are optimized simultaneously by combining all the objectives into one objective by assigning different weights to each. 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:

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

Subject to: The stability constraints given by Eq. (3a) to Eq. (3e).

where w_p is nonnegative 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 [19] on the coefficients of the digital IIR filter in Eq. (2) have been forced to satisfy by updating the coefficients with random variation [20].

3. TLOBO Algorithm

In this section, the application of TLOBO for the design of IIR digital filter is explained. TLOBO is an algorithm inspired from the social phenomena of teaching-learning in which results achieved by learners in a class depend upon the knowledge disseminated by a teacher. TLOBO explores a population of solutions to proceed to the global solution. The population is considered as a group of learners / students in a class. In TLOBO, the values of different variables to be optimized are analogous to the different subjects / courses offered to learners / students and the student score is analogous to the 'fitness value'. A teacher tries to impart knowledge among the learners, and helps students to get good marks or grades, according to his / her capability. In addition to gaining knowledge from their teacher, the learners / students being social animals also learn from interaction among themselves. Based on the above explanation, the process of TLOBO is simulated into two phases. The first phase is 'Teacher Phase' consisting of learners gaining knowledge from teacher, and the second phase is 'Learner Phase' means learners interact with each other and increase their knowledge base.

3.1. Class formulation and initialization

Assume *NL* is the number of learners in a class (population) and each learner has been assigned *S* subjects. 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:

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

In TLOBO each learner of the class is initialized with the help of random search for marks of all the subjects. Global search is applied to explore the starting point and then the starting point is perturbed in local search space to record the best starting point. The search process is started by initializing the learners using Eq. (11):

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

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*.

3.2. Opposition-based learning

The convergence rate of TLOBO has been further enhanced with the help of opposition-based learning (OBL) introduced by [21]. The concept of opposition-based learning has already been applied to accelerate reinforcement learning and back-propagation learning in neural networks [22]. The main idea behind opposition-based learning is to consider current population and its opposite population at the same time in order to select better current candidate solution. The opposition-based learning is applied to generate opposite population X_j^{op} using Eq. (12):

$$X_j^{op} = X_j^{\max} - R()(X_j^{\max} - X_j^{\min}) \ (j = 1, 2, ..., S) \tag{12}$$

Out of initial *NL* learners generated using Eq. (11) and opposite population X_j^{op} generated using Eq. (12), best *NL* learners constitute a class to initiate the process. For the global search, best learner is selected out of class of learners.

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

$$X_j^{op} = X_j^U + X_j^L - X_j \quad (j = 1, 2, ..., S) \tag{13}$$

where

$$X_j^U = \max\{ X_j ; \ (j = 1, 2, ..., S) \}$$

$$X_j^L = \min\{ X_j ; \ (j = 1, 2, ..., S) \}$$

Best *NL* learners are then selected for next cycle (iteration) of algorithm.

3.3. Fitness function evaluation

Expected fitness function, *f* is derived from the objective function. The expected fitness function of i^{th} learner of class used to solve design of IIR filter is given below:

$$f(X_i) = Minimize \ (F_i \ (X)) \qquad (i = 1, 2, ..., NL) \tag{14}$$

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

3.4. Teacher phase

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:

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

In above Eq. subscript *S* represents the number of subjects or courses, X_{old}^s is the position of learner, when this still had to learn from his teacher for increasing his level of knowledge, and consists in a vector (*1 × S*) in dimension which contains his outcomes for each particular 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 × S*) which contains the mean or average values of the class outcomes for each particular subject or course. The teaching factor (T_f) is one of the vital aspect that facilitates the convergence of TLOBO. 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.

3.5. Learner phase

The learners being social animals not only acquire the knowledge from the teacher but also interact on regular basis among themselves and share their knowledge among themselves through sharing of notes, discussions and presentations. The second phase of TLOBO emulates this sharing of knowledge by learners among themselves. 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:

$$X_{new,i}^j = \begin{cases} X_{old,i}^j + R() \times (X_{old,i}^j - X_k^j) & ; f(X_i) < f(X_k) \\ X_{old,i}^j + R() \times (X_k^j - X_{old,i}^j) & ; Otherwise \end{cases}$$

$$(j = 1, 2, ..., S) \tag{16}$$

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

3.6. Termination criteria

At the end of the learning phase, a cycle (iteration) is completed and 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 termination criterion is met. In the present work, a termination criterion of predetermined maximum iteration number is considered.

4. Simulation Results and Comparisons

In the proposed method, filter coefficients are optimized to satisfy the given design requirements in frequency domain. In the design process 5th order LP and HP IIR digital filter design examples are undertaken to investigate the performance of filter designed with TLOBO algorithm. The obtained results are compared to the performance of 3rd order LP and HP IIR filter of [7], [8] and [10]. The pass band normalized edge frequencies considered for LP and HP filter are 0.2 and 0.8 respectively. Stop band normalized edge frequencies considered are 0.3 and 0.7 respectively for LP and HP filter. For designing digital IIR filter 200 equally spaced points are set within the frequency domain $[0, \pi]$.

In the first design criterion magnitude response is approximated as absolute error in terms of L_1-norm error criterion. The objective of designing the digital IIR filters is to minimize the objective function given by Eq. (5) with the stability constraints stated by Eq. (3a) to Eq. (3e) under the prescribed design conditions. The computational results obtained by the proposed TLOBO approach are presented and compared with the results obtained by [7], [8] and [10] in Tables I and II. Magnitude response is presented in Figure 1 for the designed LP and HP filters respectively. For the IIR filter to be stable and having minimum phase, all the poles and zeros of designed filters should lie inside the unit circle. Figure 2 shows the pole-zero plots of 5th order IIR LP and HP filters respectively designed with TLOBO. It is observed from Figure 2 that maximum radii of zeros are 0.8904 and 0.9108 and maximum radii of poles are 0.9181 and 0.8976 for LP and HP filters, respectively. The best optimized 5th order numerator coefficients and denominator coefficients obtained by the TLOBO approach for LP and HP are given by Eq. (17), Eq. (18) respectively.

$$H_{LP}(z) = 0.0075068\left(\frac{(z+0.7999722)(z^2-0.3049078z+0.7927192)}{(z-0.6703151)(z^2-1.433414z+0.8428386)}\right)\times\left(\frac{(z^2-0.3049248z+0.7927386)}{(z^2-1.355091z+0.5758642)}\right) \quad (17)$$

$$H_{HP}(z) = 0.0236526\left(\frac{(z-0.5999418)(z^2+0.639706\,z+0.8295153)}{(z+0.5192546)(z^2+1.169970\,z+0.4471656)}\right)\times\left(\frac{(z^2+0.3100073\,z+0.5958582)}{(z^2+1.370906\,z+0.8056989)}\right) \quad (18)$$

TABLE I
DESIGN RESULTS FOR 5TH ORDER LP FILTER. EMPLOYING L_1-ERROR CRITERION

Method	Order	L_1-norm error	Pass-band performance (Ripple magnitude)	Stop-band performance (Ripple magnitude)
TLOBO	5	0.50544	$0.9915 \le \lvert H(e^{j\omega}) \rvert \le 1.004$ (0.0125)	$\lvert H(e^{j\omega}) \rvert \le 0.0426$ (0.0426)
TIA [10]	3	3.8157	$0.8914 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.1086)	$\lvert H(e^{j\omega}) \rvert \le 0.1638$ (0.1638)
HTGA [8]	3	3.8916	$0.8994 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.1006)	$\lvert H(e^{j\omega}) \rvert \le 0.1695$ (0.1695)
HGA. [5]	3	4.3395	$0.8870 \le \lvert H(e^{j\omega}) \rvert \le 1.009$ (0.1139)	$\lvert H(e^{j\omega}) \rvert \le 0.1802$ (0.1802)

TABLE II
DESIGN RESULTS FOR 5TH ORDER HP FILTER. EMPLOYING L_1-ERROR CRITERION

Method	Order	L_1-norm error	Pass-band performance (Ripple magnitude)	Stop-band performance (Ripple magnitude)
TLOBO	5	1.07834	$0.9965 \le \lvert H(e^{j\omega}) \rvert \le 1.005$ (0.0090)	$\lvert H(e^{j\omega}) \rvert \le 0.0709$ (0.0709)
TIA [10]	3	4.1819	$0.9229 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0771)	$\lvert H(e^{j\omega}) \rvert \le 0.1424$ (0.1424)
HTGA [8]	3	4.3413	$0.9403 \le \lvert H(e^{j\omega}) \rvert \le 1.000$ (0.0597)	$\lvert H(e^{j\omega}) \rvert \le 0.1668$ (0.1668)
HGA. [5]	3	14.5078	$0.9224 \le \lvert H(e^{j\omega}) \rvert \le 1.003$ (0.0779)	$\lvert H(e^{j\omega}) \rvert \le 0.1819$ (0.1819)

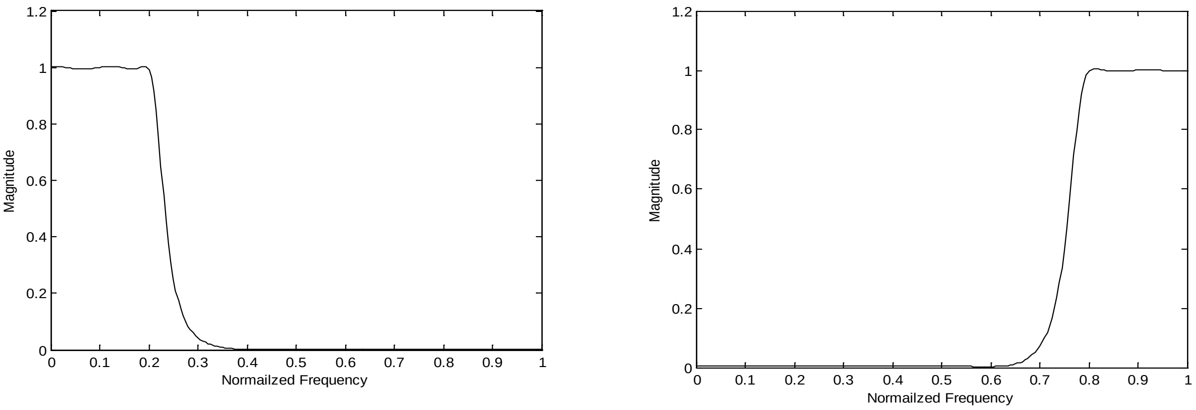

Fig 1: Magnitude response of 5th order LP and HP IIR filter using TLOBO approach employing L_1-error criterion.

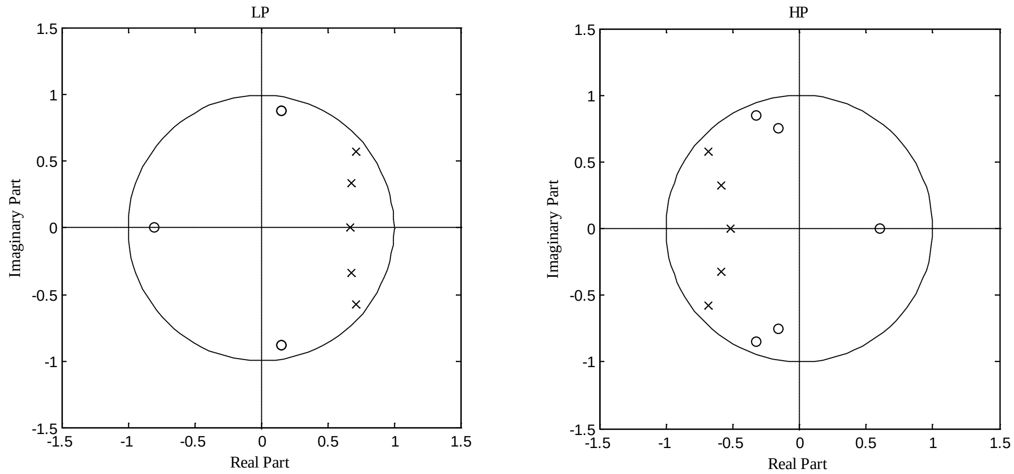

Fig 2: Pole-Zero plot of 5th order LP and HP IIR filter using TLOBO approach employing L_1-error criterion.

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. The objective function considering all the four criterion simultaneously is given by Eq. (10) by incorporating the stability constraints stated by Eq. (3a) to Eq. (3e). 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 criteria 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 LP and HP 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 III and IV. Magnitude response is presented in Figure 3 for the designed LP and HP filters respectively. Figure 4 shows the pole-zero plot of 5th order IIR LP and HP, filters respectively designed with TLOBO. It is observed from Figure 4 that maximum radii of zeros are 1.1116 and 0.9738 and maximum radii of poles are 0.9191 and 0.9190 for LP and HP filters, respectively. The best optimized 5th order numerator coefficients and denominator coefficients obtained by the TLOBO approach for LP and HP are given by Eq. (19), Eq. (20), respectively.

$$H_{LP}(z) = 0.0167532\left(\frac{(z+1.11158)(z^2-0.9609631z+0.9038306)}{(z-0.5957294)(z^2-1.262406z+0.5377362)}\right)\times\left(\frac{(z^2-0.5428474z+1.001854)}{(z^2-1.407571z+0.8447306)}\right) \quad (19)$$

$$H_{HP}(z) = 0.02819722\left(\frac{(z-0.5776086)(z^2+0.5908561z+0.8753173)}{(z+0.5711544)(z^2+1.239676z+0.5241383)}\right)\times\left(\frac{(z^2+1.011784z+0.9483423)}{(z^2+1.405046z+0.8445591)}\right) \quad (20)$$

TABLE III
DESIGN RESULTS FOR 5TH ORDER LP 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	5	0.8257	0.0747	$0.9937 \le \lvert H(e^{j\omega})\rvert \le 1.000$ (0.0065)	$\lvert H(e^{j\omega})\rvert \le 0.0242$ (0.0242)
TIA [10]	3	4.2162	0.4380	$0.9012 \le \lvert H(e^{j\omega})\rvert \le 1.000$ (0.0988)	$\lvert H(e^{j\omega})\rvert \le 0.1243$ (0.1243)
HTGA [8]	3	4.2511	0.4213	$0.9004 \le \lvert H(e^{j\omega})\rvert \le 1.000$ (0.0996)	$\lvert H(e^{j\omega})\rvert \le 0.1247$ (0.1247)
HGA. [7]	3	4.3395	0.5389	$0.8870 \le \lvert H(e^{j\omega})\rvert \le 1.009$ (0.1139)	$\lvert H(e^{j\omega})\rvert \le 0.1802$ (0.1802)

TABLE IV
DESIGN RESULTS FOR5TH ORDER HIGH PASS (HP) 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	5	2.3100	0.2013	$0.9894 \le \lvert H(e^{j\omega})\rvert \le 1.004$ (0.0154)	$\lvert H(e^{j\omega})\rvert \le 0.0591$ (0.0591)
TIA [10]	3	4.7144	0.4509	$0.9467 \le \lvert H(e^{j\omega})\rvert \le 1.000$ (0.0533)	$\lvert H(e^{j\omega})\rvert \le 0.1457$ (0.1457)
HTGA [8]	3	4.8372	0.4558	$0.9460 \le \lvert H(e^{j\omega})\rvert \le 1.000$ (0.0540)	$\lvert H(e^{j\omega})\rvert \le 0.1457$ (0.1457)
HGA. [7]	3	14.5078	1.2394	$0.9224 \le \lvert H(e^{j\omega})\rvert \le 1.003$ (0.0779)	$\lvert H(e^{j\omega})\rvert \le 0.1819$ (0.1819)

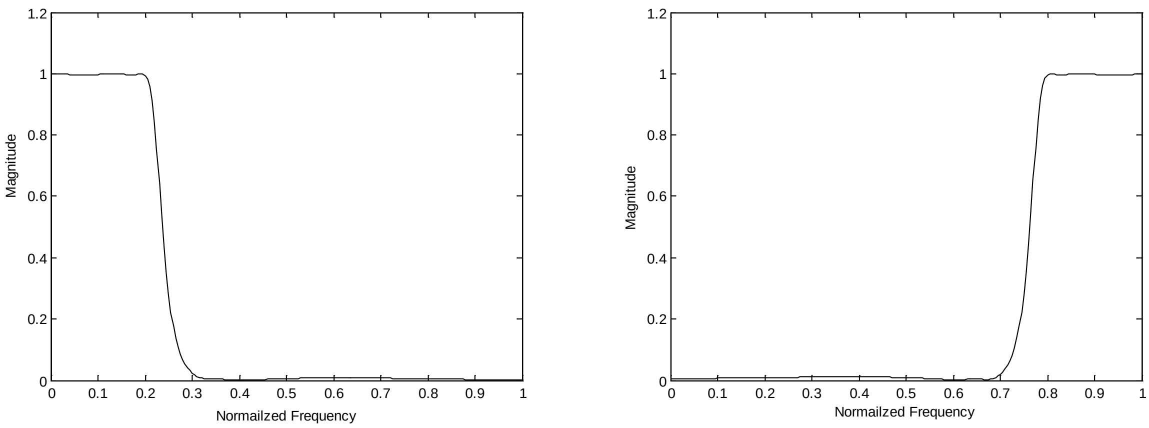

Fig 3: Magnitude response of 5th order LP and HP IIR filter using TLOBO approach employing $E_1(X)+E_2(X)+\delta_p(X)+\delta_s(X)$ criterion.

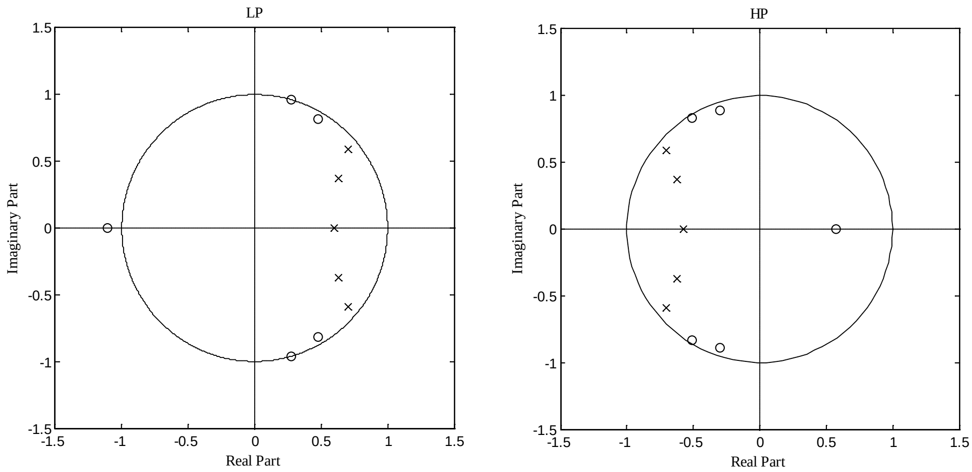

Fig 4: Pole-Zero of 5th order LP and HP IIR filter using TLOBO approach employing $E_1(X)+E_2(X)+\delta_p(X)+\delta_s(X)$ criterion

The obtained results revealed that although designed filter employing TLOBO has higher order as compared to filter design given by [7], [8] and [10], but there is significant reduction in magnitude response L_1 –error, L_2-error and magnitude of ripples in pass band and stop band as compared to the results given by [7], [8] and [10]. No doubt that due to higher order of the filter the quantization error increases which can lead to instability of the filter, but as depicted in Figure 2 the designed filter with TLOBO is stable as all poles lie inside the unit circle.

5. Conclusion

In this paper TLOBO algorithm inspired by a teaching-learning process has been applied to solve the problem of designing optimal 5th order LP and HP digital IIR filters problem. To demonstrate the effectiveness of the algorithm, the obtained results are compared with those of meta-heuristic methods. From the simulation results it is concluded that TLOBO has given considerable improvement in terms of results and convergence. The designed LP and HP IIR filter with the proposed TLOBO approach gives better performance in terms of magnitude response error and ripples in pass band and stop band. The applied TLOBO algorithm does not require any algorithm-specific parameters which makes the algorithm robust.

References:

[1] J. G. Proakis and D. G. Manolakis, *Digital Signal Processing: Principles, Algorithms, and Applications*. New Delhi: Pearson Education, Inc., 2007.

[2] A. Antoniou, *Digital Signal Processing: Signals, Systems and Filters*. New York: McGraw Hill, 2006.

[3] W.-S. Lu and A. Antoniou, "Design of digital filters and filter banks by optimization: a state of the art review," presented at the European Signal Processing Conference, Finland, 2000.

[4] S. P. Harris and E. C. Ifeachor, Automatic design of frequency sampling filters by hybrid genetic algorithm techniques, *IEEE Transactions on Signal Processing,* Vol. 46, No. 12, 1998, pp. 3304–3314.

[5] Y. Liu, *et al.*, "An application of genetic algorithms with guiding strategy in the design of digital filters " presented at the International Conference on Communication, Circuits Systems, Chengdu, China, 2004.

[6] M. Nilsson, *et al.*, Digital filter design of IIR filters using real valued genetic algorithm, *WSEAS Transactions on Circuit and Systems,* Vol. 3, No. 1, 2004, pp. 29–34.

[7] K. S. Tang, *et al.*, Design and optimization of IIR filter structure using hierarchical genetic algorithms, *IEEE Transactions on Industrial Elecronics*, Vol. 45, No. 3, 1998, pp. 481–487.

[8] J.-T. Tsai, *et al.*, Optimal design of digital IIR filters by using hybrid taguchi genetic algorithm, *IEEE Transactions on Industrial Electronics*, Vol. 53, No. 3, 2006, pp. 867–879.

[9] N. Karaboga, *et al.*, Designing IIR filters using ant colony optimisation algorithm, *Journal of Engineering Applications of Artificial Intelligence*, Vol. 17, No. 3, 2004, pp. 301–309.

[10] J.-T. Tsai and J.-H. Chou, Optimal design of digital IIR filters by using an improved immune algorithm, *IEEE Transactions on*

Signal Processing, Vol. 54, No. 12, 2006, pp. 4582–4596.

[11] C. Dai, *et al.*, Seeker optimization algorithm for digital IIR filter design, *IEEE T Ind Electron*, Vol. 57, No. 5, 2010, pp. 1710-1718.

[12] S. Chen and B. L. Luk, Digital IIR filter design using particle swarm optimisation, *Int J Model Ident Control*, Vol. 9, No. 4, 2010, pp. 327-335.

[13] P. Upadhyay, *et al.*, Craziness based particle swarm optimization algorithm for IIR system identification problem, *AEU - International Journal of Electronics and Communications*, Vol. 68, No. 5, 2014, pp. 369-378.

[14] B. Li, *et al.*, Fixed-point digital IIR filter design using two-stage ensemble evolutionary algorithm, *Applied Soft Computing* Vol. 13, No. 2013, pp. 329–338.

[15] S. K. Saha, *et al.*, Gravitation search algorithm: Application to the optimal IIR filter design, *Journal of King Saud University-Engineering Sciences* Vol. 26, No. 1, 2014, pp. 69-81.

[16] R. V. Rao, *et al.*, Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems, *Computer-Aided Design*, Vol. 43, No. 3, 2011, pp. 303–315.

[17] R. V. Rao, *et al.*, Teaching-learning-based optimization: a novel optimization method for continuous non-linear large scale problems, *Information Sciences*, Vol. 183, No. 2012, pp. 1–15.

[18] G. Vanuytsel, *et al.*, "Efficient hybrid optimization of fixed-point cascaded IIR filter coefficients," in *IEEE International Conference on Instrumentation and Measurement Technology*, Anchorage, AK, 2002, pp. 793–797.

[19] I. Jury, *Theory and Application of the Z-Transform Method*. New York: Wiley, 1964.

[20] R. Kaur, *et al.*, Real coded genetic algorithm for design of IIR digital filter with conflicting objectives, *Applied Mathematics & Information Sciences: An International Journal*, Vol. 8, No. 5, 2014, pp. 2635-44.

[21] H. Tizhoosh, "Opposition-based learning : a new scheme for machine intelligence," presented at the International Conference on Computational Intelligence for Modelling Control & Automation, Austria, 2005.

[22] S. Rahnamayan, *et al.*, Opposition-Based Differential Evolution, *IEEE Transactions on Evolutionary Computation*, Vol. 12, No. 1, 2008, pp. 64-78.