Journal of Science and Technology
ISSN: 2362-1443 (Print) 3059-9490 (Online)
2024, Vol. 4, No. 2 (Special Issue), 31-34

Optimization of FIR Filter Parameters using TLBO Algorithm

Ranjan Raj Pandey
Khwopa College of Engineering
ranjanpandey869@gmail.com

Deepa Bhattarai
Khwopa College of Engineering
deepabhattarai2058@gmail.com

Article History:
Received: 30 July 2024
Revised: 24 August 2024
Accepted: 17 December 2024

***Keywords*—FIR filter, Teaching -Optimization,Learning-Based PSO Optimization,, Low Pass.**

Abstract— **This paper introduces an approach for optimizing low pass FIR filter parameters using the Teaching-LearningBased Optimization (TLBO)algorithm. The optimization focuses on minimizing error between the desired and actual response. Performance of designed FIR digital filter have been compared with the performance of Particle Swarm Optimization (PSO) Optimization of same order and the MATLAB simulation have confirmed the superiority of the proposed design in terms of smaller pass band and stop band ripples.**

I. INTRODUCTION

Digital filters are used across a wide range of fields, from signal processing and aerospace to control systems, telecommunications, and audio/video processing. These filters act as frequency-selective devices, isolating the useful parts of an input signal within a specified frequency range. There are several traditional techniques for designing FIR filters ,including methods like the window method, frequency sampling method, and the Remez-exchange algorithm. Each of these approaches has its own advantages and disadvantages. Among them, the Remez-exchange algorithm , introduced by Parks and McClellan and commonly referred to as the PM algorithm [1], [2] is widely used for designing linear phase FIR filters. The quest for optimal digital filter design has seen remarkable advancements through the application of evolutionary optimization techniques such as Genetic Algorithms (GA) 3], cuckoo search optimization algorithm(CSA), Particle Search Optimization (PSO) [4],Artificial Bee Colony (ABC), [5] Gravitational Search Algorithm (GSA) [6] and Differential Evolution (DE) [7]. These techniques have been instrumental in enhancing control over key performance parameters, leading to more efficient and effective filter designs.

This paper explores the use of the Teaching-Learning-Based Optimization (TLBO) algorithm, an evolutionary technique, for the design of digital filters with enhanced parameter control to more closely approximate the ideal filter. In signal processing,extraneous content within the input signal can degrade the overall quality of the system. Our approach focuses on the optimization of FIR filter parameters using the TLBO algorithm. Designing FIR filters is inherently a multimodal optimization problem, where the goal is to minimize the error between the actual and desired response. This process involves iterative adjustments of filter coefficients until a specific error criterion is minimized. The primary objective of this optimization is to reduce the maximum error between the desired and actual responses, thus enhancing the filter's performance.

The proposed TLBO-based method demonstrates the potential for achieving good performance in FIR filter design, offering better control over filter parameters and improved approximation of the ideal filter.

II. FIR FILTER DESIGN

FIR filters are characterized by linear phase properties and inherent stability [8], making them a focus for researchers aiming to enhance their designs for broader practical use. To design an optimal Nth-order FIR high-pass (HP) and low -pass(LP) filter, the filter response $H(e^{j\omega})$ with filter coefficients $h[n]$,for $0 \leq n \leq N$, is approximated to the desired frequency responses $D_{LP}(\omega)$ and $D_{HP}(\omega)$. The equations for ideal lowpass and high-pass filter is defined as,

$$D_{LP}(\omega) = \begin{cases} 1, & \omega \in [0, \omega_p) \quad \text{(pass-band)} \\ 0, & \omega \in [\omega_p, \infty) \quad \text{(stop-band)} \end{cases}$$

$$D_{HP}(\omega) = \begin{cases} 0, & \omega \in [0, \omega_p) \quad \text{(stop-band)} \\ 1, & \omega \in [\omega_p, \infty) \quad \text{(pass-band)} \end{cases}$$

The approximating filter response, $H(e^{j\omega})$, is obtained by the discrete time Fourier transformation (DTFT) of the filter impulse response, $h[n]$, given by

$$H(e^{j\omega}) = \sum_{n=0}^{N} h[n] e^{-j\omega n}$$

The error function, $E(\omega)$, is computed by taking the squared difference between the magnitude response $|H(\omega)|$ and the desired magnitude response $|D(\omega)|$.

$$E(\omega) = [|D(\omega)| - |H(\omega)|]^2$$

The cost function for the above problem can be formulated as:

$$J = \sum_{k=0}^{K} W(\omega_k) E(\omega_k) \tag{1}$$

where, $W(\omega)$ is the weighting function to provide different weights for errors in different frequency bands.

The objective function is to find set of impulse response {h[0],h[1],...,h[n]} that minimizes the cost function.

$$\min_{h[n],\ n=0 \text{ to } N} \left\{ \sum_{k=0}^{K} W(\omega_k) E(\omega_k) \right\} \tag{2}$$

III. TEACHING-LEARNING-BASED OPTIMIZATION (TLBO) ALGORITHM

Teaching–learning-based optimization (TLBO) algorithm was originally introduced by Rao et al. [9] in 2011. TLBO is a population-based optimization technique inspired by the educational process in a classroom setting. TLBO mimics the teaching and learning behaviors of students and teachers to find optimal solutions to complex problems.

The TLBO algorithm comprises two main phases: the Teaching Phase and the Learning Phase. These phases simulate the process of teaching and learning, respectively, and work together to guide the population of solutions towards the optimal.

A. Learner Initialization

For a minimization optimization problem with D dimensional decision variables, let $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ represent the i-th learner (search point) and $f(X_i)$ represent the fitness function of this learner. N is the number of learners in the population. The i-th learner $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ in the class can be randomly initialized as follows:

$$x_{id} = x_{min,d} + (x_{max,d} - x_{min,d}) \times r_{id}$$

where $x_{min,d}$ and $x_{max,d}$ are the minimum and maximum bounds of the d-th decision variable, respectively, and r_{id} is a random number uniformly distributed in the interval [0,1].

B. Teaching Phase

In this phase, the teacher represents the best solution found so far. The teacher imparts knowledge to the students, which helps them improve their solutions. The process involves updating each student's position based on the teacher's position and a random factor that influences the extent of the update. The student's position is calculated by the following equation:

$$\mathbf{X}_i^{new} = \mathbf{X}_i^{old} + T \times (\mathbf{X}_{teacher} - \mathbf{X}^{mean})$$

where T is the teaching factor, which is selected between 1 and 2.

C. Learning Phase

During the learning phase, students learn from each other. This is done by sharing information among students to improve their individual solutions. Each student updates its position based on the positions of randomly selected peers in the population.

$$\mathbf{X}_i^{new} = \mathbf{X}_i^{old} + \phi \times (\mathbf{X}_j - \mathbf{X}_i^{old})$$

where ϕ is a random number between [0,1], and X_j is the position of the randomly selected student.

D. Flowchart

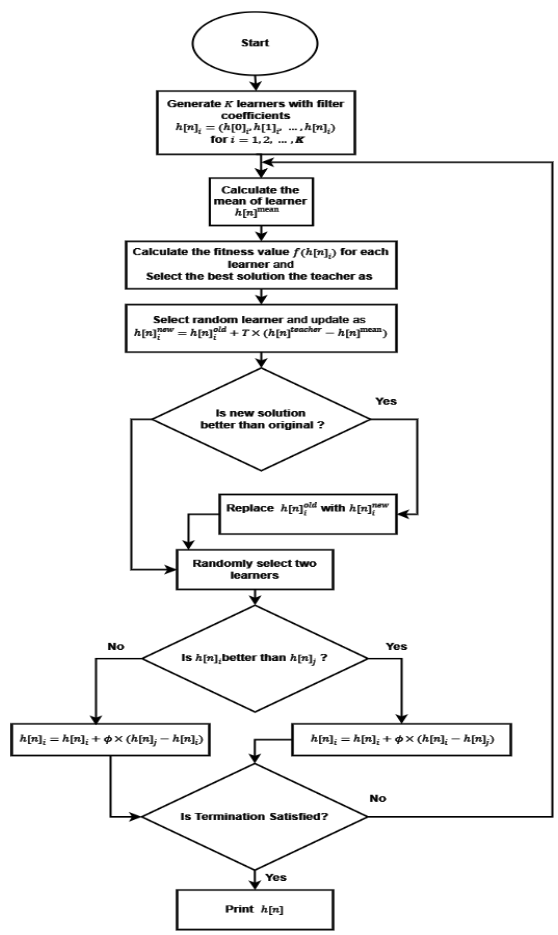

Fig. 1: Flowchart for FIR coefficients search using TLBO.

IV. SIMULATION AND RESULTS

This section presents the performed simulations in MATLAB for Low Pass FIR filter. A total of 1000 equally spaced frequency sample points have been used for full digital frequency band for all the considered designs. The filter order N is taken as 10,therefore, the number of impulse response coefficients to be optimized are 11.

TLBO and PSO optimization Algorithm is used for calculation of coefficients. Result of TLBO and PSO optimized coefficients for Low Pass filter design is presented in Table I.

TABLE I: FIR Coefficients

h[n]	Filter Coefficients	
	TLBO	PSO
h[0]	0.0859762594721208	0.0295574581638303
h[1]	$-1.43475437520212 \times 10^{-15}$	-0.0167473182624555
h[2]	-0.312764656538968	0.00599877773395289
h[3]	-0.485783480392459	0.0239811149109410
h[4]	-0.312423110924564	-0.0286641423802720
h[5]	$-1.92336732646342 \times 10^{-15}$	-0.151921846442072
h[6]	0.0856781463756855	0.00729368650585736
h[7]	$4.68838678263237 \times 10^{-12}$	0.308710979258616
h[8]	-0.0471372039560312	0.442586733801836
h[9]	$-2.07407055895330 \times 10^{-14}$	0.311131469543249
h[10]	0.0215884936868111	0.0680730871665167

Figures 2 and 3 illustrate the normalized magnitude frequency response and gain response, respectively. In all plots, the digital frequency is normalized to the range [0, 0.5].

Figure 1 presents the characteristic plot of the low pass filter designed using the Particle Swarm Optimization (PSO) algorithm. The ripples in the passband are distinctly visible.

The maximum normalized passband ripple is 0.0633, while the maximum normalized stopband ripple is 0.0839.

The performance of the filter design by TLBO have been evaluated based on their normalized magnitude response.

From the frequency response plot, it is evident that the filter exhibit a nearly flat passband of good quality, along with satisfactory stopband response. This indicates that the ripples have been minimized throughout the frequency band. According to the obtained frequency response data, the maximum stopband attenuation is 22.10 dB, the maximum normalized passband ripple is 0.0408, and the maximum normalized stopband ripple is 0.06244.

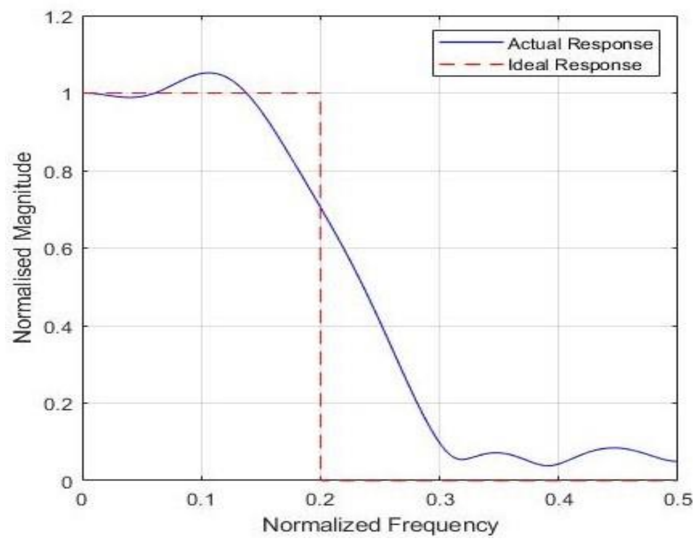

Fig. 2: Magnitude Response of FIR LP Filter using PSO.

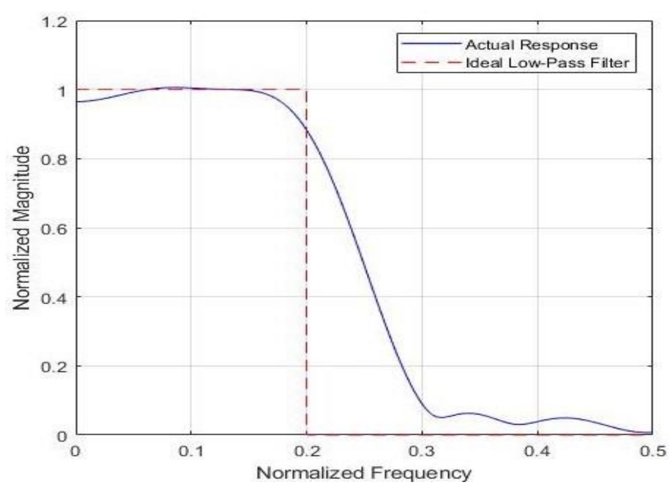

Fig. 3: Magnitude Response of FIR LP Filter using TLBO.

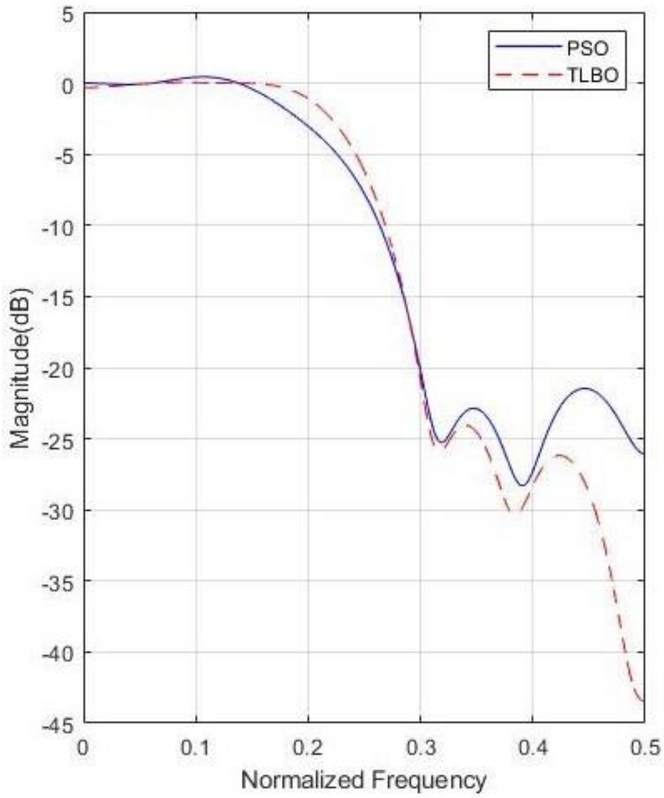

Fig. 4: Gain Response of FIR filter.

process in TLBO is more streamlined due to its structured approach of knowledge transfer between teacher and learners, leading to faster optimization.

V. CONCLUSION

In this study, we compare the convergence time and iteration speed of TLBO (Teaching-Learning-Based Optimization) with PSO (Particle Swarm Optimization). Our findings indicate that TLBO outperforms PSO in both aspects. The convergence time, which is the duration required for the algorithm to reach the optimal or near-optimal solution, is significantly shorter for TLBO.

Moreover, the number of iterations required to achieve convergence is lower in TLBO compared to PSO. The iterative

REFERENCES

[1] T. W. Parks, J. H. McClellan, Chebyshev, Approximatton for non recursive digital filters with linear phase, IEEE Transactions on Circuits Theory, 19, 189-194 (1972).

[2] J. H. Mc Clellan, T. W. Parks, L. R. Rabiner, A computer program for designing optimum FIR linear phase digital filters, IEEE Transactions on Audio and Electroacoussscs, 21, 506-526 (1973).

[3] R. S. Chauhan, S.K. Arya, An Opttmal Design of FIR Digital Filter Using Genetic Algorithm, Contemporary Computing, 51-56 (20 II).

[4] M. Najjarzadeh, A. Ayatollahi, FIR digital filters design particle swarm optimization utilizing LMS and minimax strategies, IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 129-132 (2008).

[5] R. Raju, H. K. Kwan and A. Jiang, ”Sparse FIR Filter Design Using Artificial Bee Colony Algorithm,” 2018 IEEE 61st International Midwest Symposium on Circuits and Systems (MWSCAS), Windsor, ON, Canada, 2018, pp. 956-959. S. K. Saha, R. Kar, D. Mandai, S.P. Ghoshal,

[6] Design and simulation of FIR band pass and band stop filters using gravitational search algorithm, Memetic Computing, 5 (4),311-32 (2013).

[7] N. Karaboga, B. Cetinkaya, Design of digital FIR filters using differential evolullon algorithm, Circuits Systems Signal Processing, 25 (5),649– 660 (2006).

[8] J. G. Proakis and D. G. Manolakis, Digital Signal Processing: Principles, Algorithms, and Applications, 4th ed. Pearson, 2007.

[9] R. V. Rao, V. J. Savsani, D. P. Vakharia Teachi–nlgearning-based optimization: A novel method for constrained mechanical design optimization problems, Computer -Aided Design 43(3) (2011) 303-315.