

Design of FIR Filter Using Novel Particle Swarm Optimization

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ABSTRACT

This paper presents an optimal design of digital low pass finite impulse response (FIR) filter using Novel Particle Swarm Optimization (NPSO). The design target of FIR filter is to approximate the ideal filters on the request of a given designing specifications. The traditional based optimization techniques are not efficient for digital filter design. The filter specification to be realized NPSO algorithm generates the best coefficients and try to meet the ideal frequency response. Novel Particle swarm optimization (NPSO) proposes a new equation for the velocity vector and updating the particle vectors and hence the solution quality is improved. The NPSO technique enhances its search capability that leads to a higher probability of obtaining the optimal solution. In this paper for the given problem the realization of the FIR filter has been performed. The simulation results have been performed by using the novel particle swarm optimization (NPSO) method.

Keywords : Finite Impulse Response (FIR), Particle Swarm Optimization (PSO), Novel Particle Swarm Optimization (NPSO)

I. INTRODUCTION

A filter is defined as a system that passes the band of frequencies according to the requirement. The aim of filtering is to improve the quality of the signal by removing unwanted component of signal such as noise. Different types of filters that are available are low pass filter, notch filters, high pass filter, band pass and band rejects filters etc. Filters are also classified as analog and digital. Analog filters are designed with various electronic components for example resistor, capacitor etc. and continuous time signal is used as an input. Digital filters are used in a various number of applications such as speech processing and image processing etc. The digital filter have number of advantages such as : Digital filters can be used at low frequency, the frequency response can be changed as per the requirement if it was implemented by using a programmable processor and several input signals can be filtered by one digital filter without the need to replicate hardware. The digital filters disadvantages are: speed limitation and long design and development times. Depending on the form of the unit impulse response sequence digital filters may be divided into two categories FIR and IIR filters. FIR stands for finite impulse response filter that is its impulse response is of

a finite duration and IIR stands for infinite impulse response filter which is defined as impulse response is of infinite duration. FIR filters have various number of advantages over IIR filters: FIR filters can have an exact linear phase, finite impulse response filters are stable, the design methods are generally linear, they can be realized effectively in hardware, no feedback is required which reduces the circuit complexity and hence FIR filters are always stable. There are different methods for the design of FIR filters, for example window design techniques, frequency sampling method, optimal design methods and evolutionary algorithm techniques. For the filter design the aim is to find the filter coefficients by optimizing the error function.

Window design method is the widely used method for the filter design. Some of the window functions used are Hamming window, Kaiser Window, Hanning window and Bartlet window. The Window function converts the infinite length response into the finite length response. Linear phase FIR filters are required when the time domain specifications are given .The limitation of this procedure is that the relative values of the amplitude error in the frequency bands are specified by means of weighting function and not by the deviations themselves. A different evolutionary algorithm such as genetic algorithm (GA), Differential

evolution and artificial bee colony optimization etc. has been used for the design of digital filters. Although the GA have a good performance for finding the promising regions of the search space they are inefficient in determining the local minimum in terms of the convergence speed and solution quality.

This paper present the design of FIR filter using the evolutionary algorithm: Particle Swarm Optimization (PSO) and its modified form known as Novel Particle Swarm Optimization.. The PSO's advantage lie in its simplicity to implement as well as its convergence can be controlled by few parameters. PSO algorithm generates the best coefficients that try to meet ideal frequency characteristics. The PSO is simple technique to implement and its convergence may be controlled via few parameters. The paper also compares the result of PSO and NPSO. This paper is explained as follows: Section II includes the problem statement. Section III which includes Particle Swarm Optimization Algorithm. Section IV includes the results and analysis. Section V includes the conclusion and the reference.

II. PROBLEM STATEMENT

The advantage of the FIR filter structure is that it can achieve linear phase frequency response. Hence all design methods are described in the literature deal with filters with this property.

A digital FIR filter is characterized by,

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

$$n=0,1,2,3,\dots,N$$

where N is the filter order which has N+1 number of filter coefficients, h(n). The coefficients h(n) will determines the low pass filter, high pass filter, etc. The coefficients h(n) are to be determined and N represents the order of the polynomial function. This paper presents the even order FIR low pass filter design with coefficients h(n). Hence, (N/2+1) number of h(n) coefficients are optimized, that are finally concatenated to find the required (N+1) number of filter coefficients. Magnitudes of Ideal filter in the pass band and stop band are one and zero. Error function is formed by the errors from the magnitude responses of the ideal filter and the designed filter. In each iteration of the evolutionary algorithm, fitness values of corresponding

particle vectors are calculated and are used for updating the particle vectors with new coefficients h(n). The particle vectors obtained after some number of iterations is considered to be the optimal result or best result, obtaining an optimal filter. Filter parameters which are responsible for the filter design are stop band normalized cut-off frequency ω_s , pass band normalized cut-off frequency ω_p , pass band and stop band ripples δ_p, δ_s .

In this paper, PSO and NPSO are used to obtain the magnitude filter response as close as possible to the ideal response and the particle vectors i.e. the coefficients (h_0, h_1, \dots, h_N) , are optimized.

The frequency response of the FIR digital filter is calculated as,

$$H(e^{j\omega k}) = \sum_{n=0}^N h(n) e^{-j\omega kn} \quad (2)$$

Where $\omega_k = \frac{2\pi k}{N}$. This is the FIR filter frequency response. The frequency is sampled in $[0, \pi]$ with N points.

In the present paper, error fitness function given by (3) and equation (4) has been adopted in order to achieve minimum ripples in pass band and stop band and optimum transition width. By using (3) and (4) the PSO filter design technique better results are obtained over other optimization techniques.

$$E(\omega) = G(\omega)[H_d(e^{j\omega}) - H_i(e^{j\omega})] \quad (3)$$

where $H_d(e^{j\omega})$ is the frequency response of the designed approximate filter; $H_i(e^{j\omega})$ is the frequency response of the ideal filter; $G(\omega)$ is the weighting function used to provide different weights for the approximate errors in different frequency bands.

$$J_1 = \frac{\max}{\omega \leq \omega_p} (|E(\omega)| - \delta_p) + \frac{\max}{\omega \geq \omega_s} (|E(\omega)| - \delta_s) \quad (4)$$

where δ_p and δ_s are the ripples in the pass band and stop band, respectively, and ω_p and ω_s are pass band and stop band normalized cut-off frequencies, respectively. Since the coefficients of the linear phase positive symmetric even order filter are matched, the dimension of the problem is halved. This greatly reduces the computational burdens of the algorithms.

PSO algorithm tries to minimize this error fitness J and hence optimizes the filter performance. J involves summation of all the absolute errors for the whole frequency band and thus, minimization of J gives much higher stop band attenuation and lesser stop band ripples and transition width is also reduced.

III. Optimization Technique Employed

A. Particle Swarm Optimization

PSO is a population based optimization algorithm put forward originally by Kennedy and Eberhart. It is developed from swarm intelligence and is inspired by social behavior of bird flocking or fish schooling. PSO is an optimization algorithm with implicit parallelism which can be easily handled with the non-differential objective functions. It is based on the natural process in which swarm of particles to share individual knowledge. Bird flocking or fish schooling optimizes a certain objective function. PSO algorithm uses a number of particle vectors moving around in the solution space searching for the optimist solution. Every particle in the algorithm acts as a point in the N-dimensional space. Each particle keeps the information in the solution space for each iteration and the best solution is calculated, that has obtained by that particle is called personal best (pbest). This solution is obtained according to the personal experiences of each particle vector. Another best value that is tracked by the PSO is in the neighborhood of that particle and this value is called gbest among all pbests.

Each particle tries to modify its position according to the following information:

- The distance between the current position and the Personal best.
- The distance between the current position and the Group best.

Mathematically velocity of the particle vectors is given according to the following equation:

$$v_i^{k+1} = w^{k+1} + c_1 \times rand_1 (pbest_i - x_i^k) + c_2 \times rand_2 \times (gbest^k - x_i^k) \quad (5)$$

where v_{ik} is the velocity of the i^{th} particle at k^{th} iteration; c_1 and c_2 are the weights of local information and global information; $rand_1$ and $rand_2$ are the random numbers between 0 and 1; x_i^k is the current position of the i^{th} particle at k^{th} iteration; $pbest_i$ is the personal best of the i^{th} particle at k^{th} iteration; $gbest^k$ is the group best at k^{th} iteration. The Particle position in the solution space is given by the following equation:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (6)$$

The first term of (5) is the previous velocity of the particle vector. The second term is the personal influence of the particle vector and third term is the social influence of the group. Without the second and third terms the particle vector will keep on flying in the same direction until it hits the boundary.

The parameter w^{k+1} is the inertia weight and it is used to balance global exploration and local exploitation of the solution space.

$$w^{K+1} = w_{max} - (w_{max} - w_{min}) * \frac{(k+1)}{k_{max}} \quad (7)$$

Where $w_{max}=1$; $w_{min}=0.4$; k_{max} = Maximum number of the iteration cycles.

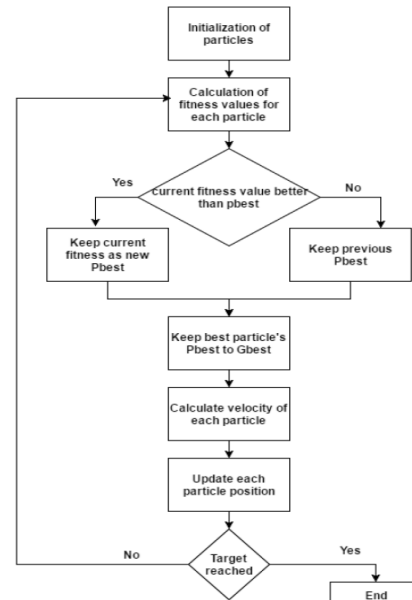


Figure 1. PSO Flow Chart

B. Novel Particle Swarm Optimization

The drawback of the conventional PSO used for the generation of optimal coefficients of filter design problem is that it results in sub-optimality problem. In general, the initial solutions are usually far from the global optimum and hence the larger inertia weight w may be proved to be beneficial. Large inertia weight enables the PSO to explore globally and small inertia weight enables the PSO to explore locally. This inertia weight w plays the important role of balancing the global and local exploration abilities. The value of w for all particles will decrease at the same time as the iteration number increases and is calculated using the following expression

$$w = w_{max} - (w_{max} - w_{min}) \times \frac{iter}{iter_{max}} \quad (8)$$

where, w_{max} and w_{min} are the initial and final weight, respectively. The standard PSO has oscillatory problem and is easy to be trapped in local optima if a promising area where the global optimum resides is not identified at the end of the optimization process. The further development of conventional

PSO is used to improve the possibility of exploring the search space where the global optimal solution exists. A slightly different approach further provides a well balanced mechanism between global and local exploration abilities. The proposed weighting function is defined as follows:

$$w = w_{max} - (w_{max} - w_{min}) \times \frac{iter}{iter_{max}} \quad (8)$$

where, $\max w$ and $\min w$ are the initial and final weight, respectively. The standard PSO has oscillatory problem and is easy to be trapped in local optima if a promising area where the global optimum resides is not identified at the end of the optimization process. The proposed weighting function is defined as follows:

$$w = \frac{2}{(w_1 + w_2) - 2 + \sqrt{(w_1 + w_2)^2 - 4(w_1 + w_2)}} \quad (9)$$

The significance of control of inertia weight w in the PSO algorithm is also retained to increase the possibility of occurrence of escaping from local optimal solutions. Update the velocities and positions of the particles. The velocity of the particle vector is updated according to

$$V_{qi}^{k+1} = w_{qi} \times V_{qi}^k + C_1 \times rand \times (pbest_{qi}^k - X_{qi}^k) + C_2 \times rand \times (gbest_i^k - X_{qi}^k) \quad (10)$$

Eq. (11) is applied to update the position of the particles.

$$X_{qi}^{k+1} = X_{qi}^k + V_{qi}^{k+1}; q=1,2,\dots;i=1,2,\dots \quad (11)$$

IV. Results and Analysis

Analysis of Magnitude response of low pass FIR filter
The MATLAB simulation is used to design the FIR filter. The order of the filter is 20 and the number of filter coefficient is 21. PSO and NPSO algorithm is run for 40 times to get the best filter coefficients. The error fitness values are found and compared with previous values. Position of the particles is updated.

TABLE 1.
VARIOUS PSO AND NPSO PARAMETERS

Parameters	PSO	NPSO
Population Size	50	50
Iteration Cycle	1500	1500
C_1	2.05	2.05
C_2	2.05	2.05
W_{max}	1.0	1.0
W_{min}	0.4	0.4
W_1	-	2.05
W_2	-	2.05
nVar	20	20
VarMin	-1	-1
VarMax	1	1
δ_p	0.1	0.1
δ_s	0.01	0.01

TABLE 2
OPTIMIZED COEFFICIENTS OF THE FIR LP
FILTER OF ORDER 20

h(N)	PSO	NPSO
h(1)=h(21)	0.0079526303460560 0	0.0064356164633190 4
h(2)=h(20)	0.0306157467568072	0.0605138023404362
h(3)=h(19)	0.0410774194030853	-0.188001359581990
h(4)=h(18)	0.0200852034291039	-0.328113934819792
h(5)=h(17)	0.0028425311025506 9	-0.357641163419596
h(6)=h(16)	0.0380638369163607	-0.216702823876734
h(7)=h(15)	0.109193579904844	0.005691582833904
h(8)=h(14)	0.137060027327504	0.141770695578045
h(9)=h(13)	0.0902045249184267	0.106318835546596
h(10)=h(12)	0.0490145500040202	- 0.0244464718595074
h(11)	0.006466789394804	-0.253304876979477

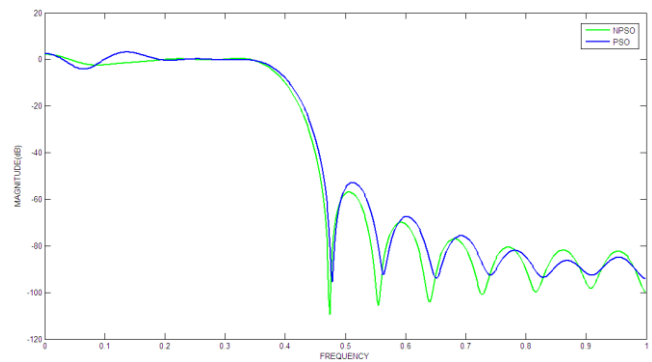


Figure 1. dB PLOTS FOR THE FIR LP FILTER OF ORDER 20

From the results in the stop band region filter designed by the NPSO method produce better response than the PSO method. NPSO method has minimum ripple magnitude in the stop band region.

IV. CONCLUSION

This paper presents the FIR filter design using particle swarm optimization algorithm. The simulation results obtained from particle swarm optimization compared with the novel particle swarm optimization method. It is found that NPSO technique gives better results to design FIR filter. By using the NPSO algorithm desired magnitude response is obtained and the best coefficients are found. Filter designed by the NPSO method produce better response in terms of minimum stop band ripple magnitude and maximum stop band attenuation.

V. REFERENCES

- [1]. T.W. Parks, C.S. BURUS, Digital Filter Design, Wiley, Network, 1987.
- [2]. T.W. Parks, J.H. McClellan, "Chebyshev approximation for non-recursive digital filters with linear phase," IEEE Trans. CircuitsTheory CT-19, pp. 189–195, 1972.
- [3]. J.H. McClellan, T.W. Parks, L.R. Rabiner, "A computer program for designing optimum FIR linear phase digital filters," IEEE Trans.Audio Electroacoustic., AU-21, pp. 506–525, 1975.
- [4]. L.R. Rabiner, "Approximate design relationships for low pass FIR digital filters," IEEE Trans. Audio Electroacoustic, AU-21, pp. 456–460, 1973.
- [5]. G. Liu and G. He, "Design of Digital FIR filters Using Differential Evolution Algorithm Based on Reversed Gene", IEEE Congress on Evolutionary Computation, pp. 1-7, July 2010.
- [6]. N. Karaboga, "A new design method based on artificial bee colony algorithm for digital IIR filters", Journal of the Franklin Institute, 346, (4), pp.328-347, 2009.
- [7]. N.E. Mastorakis and M.N.S. Swamy, "Design of Two Dimensional Recursive Filters Using Genetic Algorithms," IEEE Transaction on circuits and systems I-Fundamental Theory and Applications, 50, pp.634-639, 2003.
- [8]. J.I. Ababneh, M.H. Bataineh, "Linear phase FIR filter design using particle swarm optimizations", Digital signal processing, 18,657-669, 2008.
- [9]. M. Najarzadeh, A. Ayatollahi, "FIR Digital Filters Design: Particle Swarm Optimization Utilizing LMS and Minimax Strategies", International symp. On Signal Processing and Information Technology, ISSPIT, pp.129-132, 2008.
- [10]. J. Kennedy, R. Eberhart, "Particle Swarm Optimization," IEEE int. Conf. On Neural Network, pp.1942-1948, 2005.