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Optimal Design of Low Pass FIR Filter Using Modified PSO Approach

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Abstract— *An efficient method of digital FIR filter design using PSO with time varying inertia weight and acceleration coefficients is presented in this paper. Existing methods of optimal filter design using Genetic algorithm, simple pso are not efficient for accurate design so iteration varying inertia weight and acceleration parameters based approach is used for design. The proposed approach is used to find the optimal solution of the objective function used in this paper. The objective function is the mean square error between the actual filter and the ideal filter. By using the proposed optimization algorithm the deviation of the actual filter from the ideal filter is to be minimized. PSO-TVAC and PSO-NTVE approach uses a new equation to update the position and velocity of the particles according to iteration number. In this way particle moves towards the desired solution or optimal solution with in the search space. The simulation results are shown for the design of the filter and convergence behavior with respect to iteration cycle.*

Keywords: *Low pass fir filters; Particle swarm optimization; fitness function; Digital filters; time varying acceleration coefficients*

1. INTRODUCTION

PSO algorithm is based on randomized search is used to design the optimal digital fir filter. A filter is defined as a kind of network that passes the band of frequency according to the requirement. The main aim of filtering is to improve the quality of the signal by removing the noise. Different types of filters are available for example low pass filter, notch filters, high pass filter, band pass and band rejects filters. Filter also classified as analog and digital. Analog filters are designed with various electronic components for example resistor, capacitor, transistor etc. and continuous time signal is used as an input.[1] Digital filters play a major role in DSP. Digital filters are used in a number of applications such as speech processing and image processing etc. Digital filters have number of advantages: Digital filters can be used at very low frequency, Performance of the digital filters do not change with the environmental conditions like temperature Changes, the frequency response can be changed as per the requirement if it is implemented using a programmable processor [3].The major disadvantages of digital filters are: speed limitation, Finite word length effects. Depending upon the impulse response sequence digital filters may be divided in to two categories FIR and IIR filters. FIR stands for finite impulse response filter that is its impulse response is of finite duration and IIR stands for infinite impulse response filters which is defined as impulse response is of infinite duration. Another classification is symmetrical and asymmetrical fir filters. The important condition for symmetrical fir filter is h(n) = h(N-1-n) and for asymmetrical filter h(n) = - h(N-1-n). FIR filters have number of advantages over IIR filters:

i. Their phase response can be exactly linear.
ii. Finite impulse response filters are stable.
iii. The design techniques are usually linear.
iv. They can be efficiently implemented in hardware.
v. No feedback is required which reduces the circuit complexity.
vi. All the poles are located inside the unit circle due to this reason fir filters are always stable.

There are various methods for fir filter design for example window design technique, frequency sampling method and optimum equiripple design techniques. For the filter design the main aim is to find the filter coefficients by optimizing the fitness function. Window design is the widely used technique for the filter design. Various window functions are Kaiser Window, Hamming window, Hanning window and Bartlett window functions. The Window functions convert the infinite length response in to finite length response. This paper is organized as follows: Section II shows the problem statement. Section III gives the literature review and proposed Method which includes Particle Swarm Optimization Algorithm. Section IV shows the results and analysis and last section V contains the conclusion and the references.

2. PROBLEM STATEMENT

A transfer function for FIR filter is

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

Consider that $h(n) \neq 0$ for n = 0, 1 ..N in which N denotes the order of fir filter so the number of filter coefficients is N+1. Filter coefficients h (n) that decides the type of filter. In the algorithm each particle represents the filter coefficients [10].

The mean square error between actual and the ideal filter is the error function which is used to calculate the value of the individual particle. In this the deviation from the ideal filter is minimized by optimizing the filter coefficients. The frequency response can be defined as

$$H\,(e^{-j\omega k}) = \sum_{n=0}^{N-1} h(n)e^{-j\omega kn} \quad (1)$$

For k = 0, 1, 2 .N-1

Where $\omega_k = 2\pi k / N$

The fitness function is the mean square error and given below.

$$J_1 = \sum_{k=1}^{k} |H\text{ actual } (e^{-j\omega k}) - H\text{ ideal } (e^{-j\omega k})|^2$$

lso Error (w) = E [e^2 (k)] (2)

The various ideal filters has the magnitude response of the form is given by,

$$\begin{aligned}
H_i(\omega) &= 1 \text{ for } 0 \le \omega \le \omega_c \\
&= 0 \text{ otherwise} \\
H_i(\omega) &= 0 \text{ for } 0 \le \omega \le \omega_c \\
&= 1 \text{ otherwise} \\
H_i(\omega) &= 1 \text{ for } \omega_p \le \omega \le \omega_s \\
&= 0 \text{ otherwise} \\
H_i(\omega) &= 0 \text{ for } \omega_p \le \omega \le \omega_s \\
&= 1 \text{ otherwise} \quad (3)
\end{aligned}$$

Where ω_c denotes cutoff frequency for LP or HP filter, and ω_p and ω_s is the pass band and stop band frequency for BP and BS filters respectively. The other fitness function can be used given by

$$J_2 = \sum_{\omega\epsilon\omega p} \text{abs}\,[\text{abs}\,(|H\,d\,(\omega)\,|1) - \delta\,p] + \sum_{\omega\epsilon\omega s}[\text{abs}\,(|H\,d\,(\omega)\,| - \delta\,s)] \quad (4)$$

Where J_2 represents the fitness function to be minimized using the pso. In the filter design the important parameters are cutoff frequency, pass band frequency, stop band edge frequency and ripples in both the region.

3. LITERATURE REVIEW

3.1 Particle Swarm OptimizatioN

PSO is a type of swarm intelligence that depends on birds-flocking and fish-schooling behavior and can be used for various applications of science and engineering [11]. It is similar to genetic algorithms but require less memory for computations and a small program for its implementations. The L-th particles move in the D-dimensional search space with initial position and velocity given by the following equations

$$X_L = x_{L1}\, x_{L2} \quad x_{LD} \quad (5)$$

$$V_L = v_{L1} v_{L2} \quad .....v_{LD} \quad (6)$$

Their positions and velocity are changed as per equations given below

$$\begin{aligned}
&V_{LD}\,(k+1) = \omega\,(k) * V_{LD}\,(k) + c_1 * r_1 * (P_{LD}\,(k) - X_{LD}\,(k) \\
&+ c_2 * r_2\,(P_g - X_{LD}\,(k)) \text{ for } L=1, 2 \text{ .. } M \\
&X_{LD}\,(k+1) = X_{LD}\,(k) + V_{LD}\,(k+1) \quad (7)
\end{aligned}$$

To get quick convergence, the inertia weight (ω) change as per the given equation which decreases linearly with the iteration number.

$$\omega(k) = \omega_{min} + \frac{\text{maxit} - \text{iter}}{\text{maxit}} \cdot (\omega_{max} - \omega_{min}) \quad (8)$$

In this pso approach, inertia weight ω decreases linearly from maximum value to min. value as per current iteration therefore this approach is called as PSO-TVIW [15].

If the inertia weight, cognitive parameter (c_1) and social parameter (c_2) varies as per the following equations

$$\begin{aligned}
\omega(k) &= \omega_{min} + \left(\frac{\text{maxit} - \text{iter}}{\text{maxit}}\right) \cdot (\omega_{max} - \omega_{min}) \\
c_1\,(k) &= c_1^{min} + \left(\frac{\text{maxit} - \text{iter}}{\text{maxit}}\right) \cdot (c_1^{max} - c_1^{min}) \\
c_2\,(k) &= c_2^{max} + \left(\frac{\text{maxit} - \text{iter}}{\text{maxit}}\right) \cdot (c_2^{min} - c_2^{max}) \quad (9)
\end{aligned}$$

Therefore pso approach is termed as PSO with time varying acceleration coefficients PSO-TVAC.

If the inertia weight, social parameter (c_2) and cognitive parameter (c_1) varies as per the following equations

$$\begin{aligned}
\omega(k) &= \omega_{min} + \left(\frac{\text{maxit} - \text{iter}}{\text{maxit}}\right)^a \cdot (\omega_{max} - \omega_{min}) \\
c_1\,(k) &= c_1^{min} + \left(\frac{\text{maxit} - \text{iter}}{\text{maxit}}\right)^b \cdot (c_1^{max} - c_1^{min}) \\
c_2\,(k) &= c_2^{max} + \left(\frac{\text{maxit} - \text{iter}}{\text{maxit}}\right)^c \cdot (c_2^{min} - c_2^{max}) \quad (10)
\end{aligned}$$

Then this pso approach is termed as PSO-NTVE. In this approach inertia weight ω decreases from minimum value to maximum value. Another parameter c_1 increases from low value to high value and c_2 decreases from maximum value to minimum value [16-17]. The constants a, b and c mentioned in the proposed pso algorithm motivate particles to move through the D-dimensional search space rather than to form a cluster near a local optimum space due to this fact convergence behavior towards the optimum solutions is enhanced. To find the optimal solutions various combinations of a, b and c is tested.

Possible cases	a	b	C
Case I	0.5	0.5	0.5
Case II	0.5	1.0	0.5
Case III	0.5	1	1

Where
M population size;
k current iteration number;
x_{LD} position of Lth particle at kth iteration;
v_{LD} velocity of Lth particle at kth iteration
P_g global best per iteration;
$P_{LD}(k)$ local best per iteration;
c_1, c_2 cognitive and social parameter lies between 0.5 - 2.05 , called acceleration coefficients.
r_1, r_2 random values generated between 0 and 1;
$\omega(k)$ inertia weight at kth iteration;
ω_{max}, ω_{min} max. And min. value of inertia weight;
Maxit maximum number of iteration;
iter current iteration;

PSO ALGORITHM
The various steps used for implementation of the PSO algorithm are explained below:

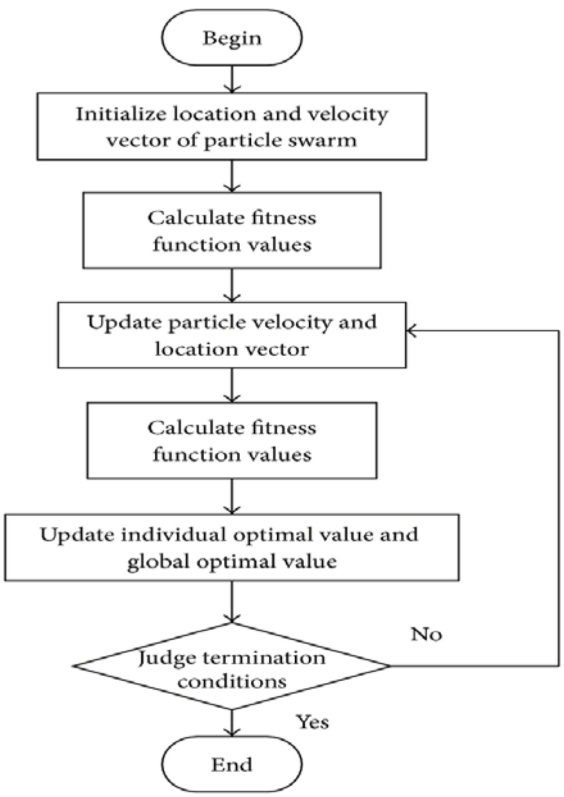


Fig. 1: Flow chart of PSO

- Step1. Initialize random particles.
- Step2.Calculate fitness value for every particle and find out the individual best (personal best).
- Step3. Is current fitness value better than personal best if yes assign current fitness as new pbest else keep previous best .
- Step4. Assign best particle's personal best as global best Pg.
- Step5. Again update the position & velocity of all the particles using equation (3).
- Step6. Repeat steps 2 to 5 until the maximum iteration is reached.

4. RESULTS AND ANALYSIS

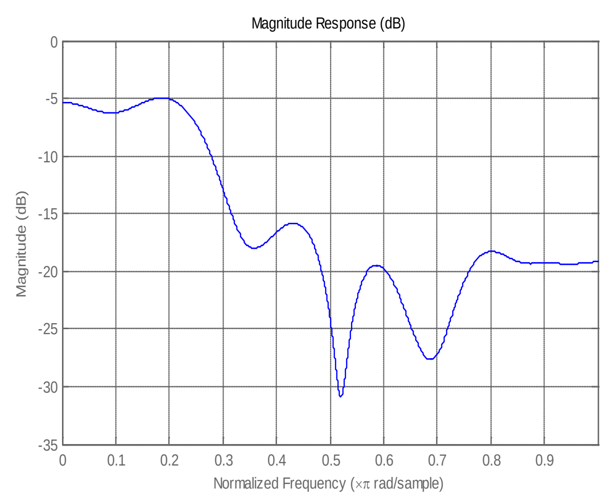
A. Magnitude Response of LP FIR filter

The MATLAB simulation is used to design the filter. The order of the filter is 20 and the number of filter coefficient is 21.Algorithms is run for 40 times to get the optimal solutions. The fitness values is calculated and compared with previous one so the fitness value is updated iteration by iteration.

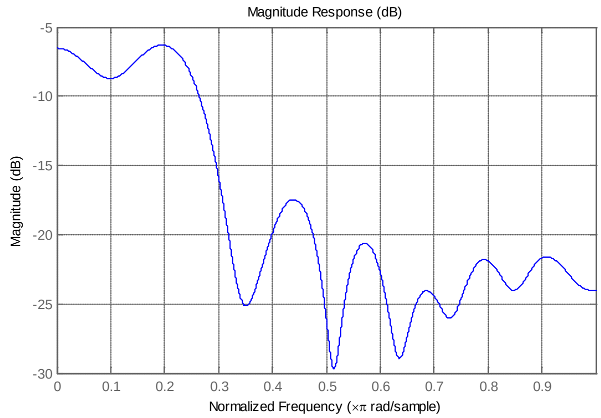
Table 1: Shows the various parameters used in optimization algorithms.

Parameters	PSO
Population size	30
Iteration Cycle	40
C_1 min-max	0.5-2.05
C_2min-max	0.5-2.05
Min v_i	0
Max v_i	1
Max w	1
Min w	0.4

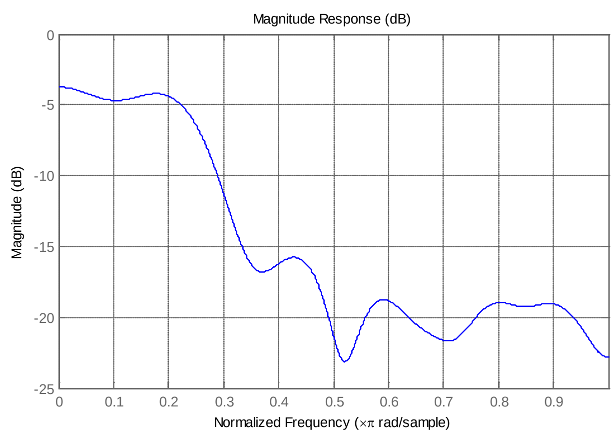
Magnitude response of LP filter using PSO-TVIW algorithm is shown below



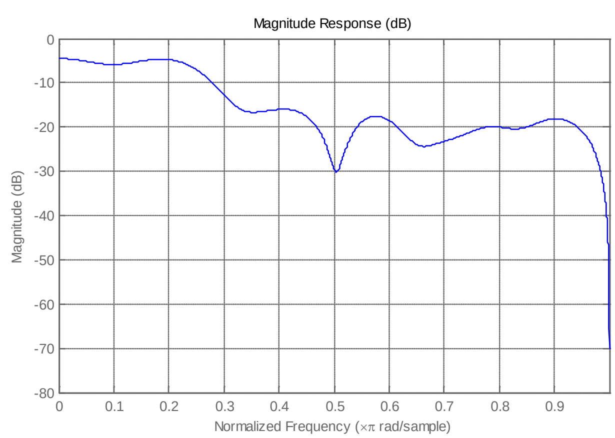
Magnitude response for PSO-TVAC algorithm is shown below



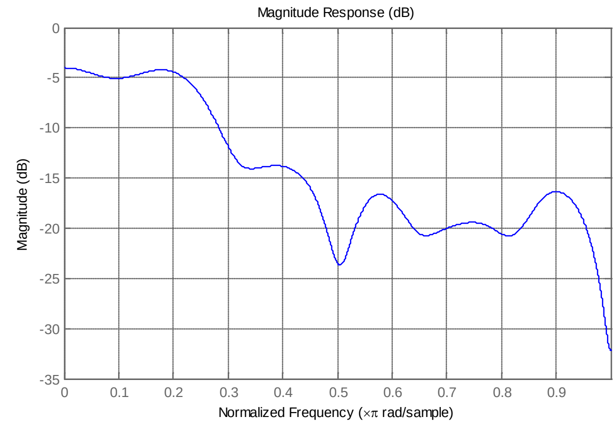
Magnitude response using PSO-NTVE algorithm for case I is shown below



Magnitude response using PSO-NTVE algorithm for case II is shown below



Magnitude response using PSO-NTVE algorithm for case III is shown below



Magnitude response using PSO-NTVE algorithm for case IV is shown below

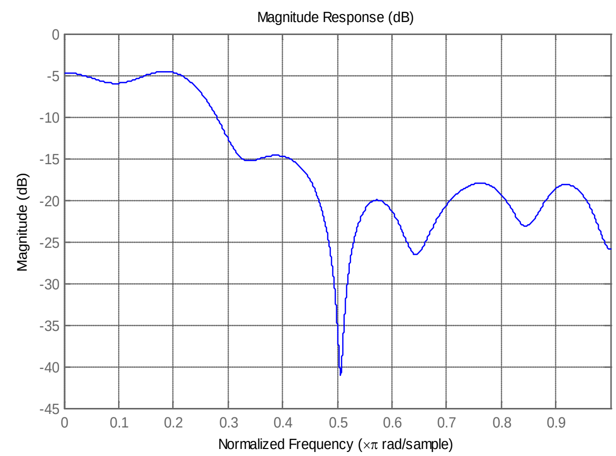
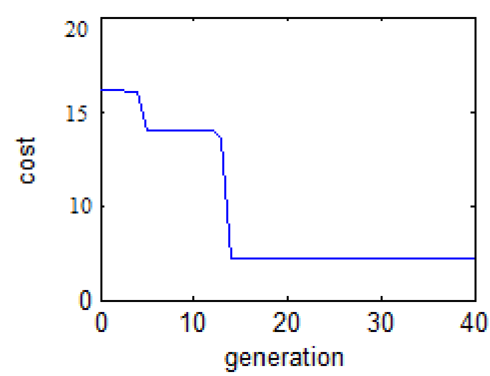


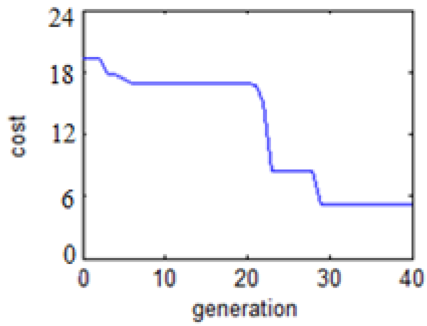
Fig. 2: All the Magnitude plots of low pass FIR filter with PSO algorithm shown below N= 20 and w_c=0.3

B. convergence behavior of PSO:

I. convergence plot for PSO-TVIW algorithm



II. Convergence plot for PSO-TVAC algorithm



III. Convergence plot for PSO-NTVE algorithm

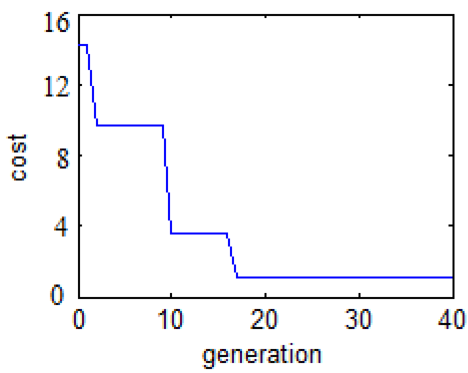


Fig. 4: Plot of fitness function values vs. iteration cycle for PSO.

5. CONCLUSIONS

The PSO randomly efficient optimization algorithm using inertia weight, social and acceleration parameters varies with iteration approach converge more rapidly than the simple pso and PSO-TVIW algorithm and hence number of iterations required to optimize the fitness function is decreased. The pso converges at lower fitness value in less iteration using the proposed algorithm. The simulation done in this paper verifies the results of proposed method of optimal design of fir filter.

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