Taylor & Francis
Taylor & Francis Group

Automatika

Journal for Control, Measurement, Electronics, Computing and Communications

ISSN: 0005-1144 (Print) 1848-3380 (Online) Journal homepage: https://www.tandfonline.com/loi/taut20

Variant of the charged system search algorithm for the design of optimal linear phase finite impulse response filters

R. P. Meenaakshi Sundhari & S. N. Deepa

To cite this article: R. P. Meenaakshi Sundhari & S. N. Deepa (2019) Variant of the charged system search algorithm for the design of optimal linear phase finite impulse response filters, Automatika, 60:3, 266-273, DOI: 10.1080/00051144.2019.1570632

To link to this article: https://doi.org/10.1080/00051144.2019.1570632

Published online: 16 Apr 2019.

AUTOMATIKA
2019, VOL. 60, NO. 3, 266–273
https://doi.org/10.1080/00051144.2019.1570632

FORTHCOMING SPECIAL ISSUE: COMPUTATIONAL INTELLIGENCE AND CAPSULE NETWORKS

OPEN ACCESS Check for updates

Variant of the charged system search algorithm for the design of optimal linear phase finite impulse response filters

R. P. Meenaakshi Sundhari[a] and S. N. Deepa [b]

[a]Department of Electronics and Communication Engineering, PA College of Engineering and Technology, Coimbatore, India; [b]Department of Electrical and Electronics Engineering, Anna University, Coimbatore, India

ABSTRACT

Digital signal filtering is one of the prime area which is frequently used in practical applications. In the class of digital filters, the prominent filters include – filters with finite impulse response (FIR) and filters with infinite impulse response (IIR). Low pass, high pass, band pass and band stop filters are the different types of filters that are currently employed for carrying out filtering actions. Filters are used for practical applications to reduce the noise incurred while processing the signals received, whether it may be an audio signal, video signal, bio-medical signal and so on. The key features for the design of filters include the optimization of coefficients and in turn the design of coefficients is based on attaining maximum stop band attenuation with less ripple rates. This paper proposes the soft computing based wavelet concept being introduced in the charged system search algorithm at the updation process. The scaling factor in the updation equation is implemented with a wavelet introduced to improve the exploration and exploitation capability of the algorithm. This introduction of wavelet into the algorithm results in faster convergence of the algorithm and proves its effectiveness in comparison with that of the other approaches as available in the literature.

ARTICLE HISTORY
Received 23 October 2018
Accepted 9 January 2019

KEYWORDS
Optimal linear phase; charged system search algorithm; wavelets; soft computing approach; filter design; optimization algorithm

1. Introduction

In this paper, work is carried out on the design of linear phase optimal FIR filter types. On analysing the growing evolutionary optimization techniques and carrying out an extensive literature survey, it was observed widely all the evolutionary techniques – genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE), bee colony algorithm, gravitational search algorithm (GSA), harmony search algorithm (HSA), Tabu search algorithm, fuzzy adaptive simulated annealing, bacterial foraging optimization algorithm and variants and hybrid approaches of these algorithms – have been actively utilized in order to compute the optimal FIR filter coefficients for all types of filters. Few contributions made in the design of optimal filter coefficients for FIR filters employing evolutionary optimization techniques are as given below.

Fang et al. [1] suggested quantum-behaved particle swarm optimization (QPSO) for the FIR digital filters design. Compared to the original PSO the presented QPSO was found to be a global stochastic searching technique that can searche for the global optima of the problem more rapidly. Teixeira and Romariz [2], suggested design optimum non-linear phase finite impulse response digital filters adapting computational intelligence numerical optimization techniques. The filter magnitude and group delay approximation will be assigned as a classical approximation problem, where a non-linear function of multiple variables must be reduced.

Examples of 1-D FIR filters were developed by Najjarzadeh and Ayatollahi [3] based on the proposed methodologies to prove the usefulness and efficiency and also analysed impact on convergence behaviour and optimal resultant frequency response of various populations and iteration in the PSO based FIR filter design. Karaboga [4] pointed out the artificial bee colony (ABC) algorithm for global optimization in IIR filters design, the ABC algorithm simulating the intelligent foraging behaviour of honey bee swarm.

The constriction factor based PSO algorithm produces a set of filter coefficients and tries to satisfy the required ideal frequency characteristic, for the given problem, the realization of the FIR band pass filters of various order has been conducted by Kar et al. [5]. Two objective functions (error metrics) are reduced, the first one is based on stop and pass band ripple and other one studies the mean square error between the ideal and actual designed filter in the work developed by Ghosh et al. [6].

The novel PSO as developed by Mondal et al. [7] has improved solution quality by novel definition for the

CONTACT R. P. Meenaakshi Sundhari rpmeenaakshi@gmail.com Department of Electronics and Communication Engineering, PA College of Engineering and Technology, Coimbatore, India

velocity vector and swarm updating. The gravitational search algorithm assured the exploitation step and it is significantly free from premature convergence so as to design the required filters as proposed by Saha et al. [8].

The above said studies focus on the design of FIR filters by evaluating the respective fitness considered. Related to this, in this paper attempt is taken to minimize the execution time, maximize the top band attenuation, minimize the stop band ripple and increase the convergence time of the algorithm by developing a novel wavelet based charged system search algorithm. The basic charged system search algorithm is widely employed for solving non-deterministic polynomial hard optimization problems. In this paper, a first attempt is taken to evolve a new wavelet based charge system search algorithm and apply it for digital signal processing application. The newly proposed approach has proven to be better in comparison with the solutions available in the literature.

2. Problem definition

Basically, digital filters are classified into infinite impulse response (IIR) filters and finite impulse response (FIR) filters. The FIR [9] filter's impulse response is represented by the following equation:

$$H(z) = h(0) + h(1)z^{-1} + h(2)z^{-2} + h(3)z^{-3} + \cdots + h(N)z^{-N} \quad \text{i.e.,}$$

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

and $h(n)$ specifies filter's impulse response. The impulse response difference equation for the filter is as given below

$$y(n) = h(0)x(n) + h(1)x(n-1) + \ldots + h(N)x(x-N) \tag{2}$$

In Equation (2), N is the filter order and N+1 specifies the number of filter coefficients. The FIR filter frequency response is computed using

$$H(\omega_k) = \sum_{n=0}^{N} h(n)e^{-j\omega_k n} \tag{3}$$

where $\omega_k = (2\pi k/N)$ and $H(\omega_k)$ specify Fourier transform. With respect to $H_d(\omega)$ and $H_i(\omega)$, Table 1 presents the magnitude response of the designed filters in an ideal case.

The fitness function formulated in this paper is [10]

$$E(\omega) = G(\omega)[H_d(e^{j\omega}) - H_i(e^{j\omega})] \tag{4}$$

In the above, weighting function is $G(\omega)$ and this parameter results in weight values that perform error approximation at various frequency bands. The main drawback of the Parks & McClellan (PM) algorithm is the fixed ratio between pass band and stop band ripple. Henceforth, the PM algorithm's error criterion is modified as presented in Equation (5).

Table 1. Filter response.

Filter type	Magnitude response (ideal filter)
Low pass	$\begin{cases} 1 & \text{for } 0 \le \omega \le \omega_c \\ 0 & \text{otherwise} \end{cases}$
High pass	$\begin{cases} 0 & \text{for } 0 \le \omega \le \omega_c \\ 1 & \text{otherwise} \end{cases}$
Band pass	$\begin{cases} 1 & \text{for } \omega_{pl} \le \omega \le \omega_{ph} \\ 0 & \text{otherwise} \end{cases}$
Band stop	$\begin{cases} 0 & \text{for } \omega_{pl} \le \omega \le \omega_{ph} \\ 1 & \text{otherwise} \end{cases}$

Notes: ω_c – high pass and low pass cut off frequency. ω_{pl} and ω_{ph} – band pass and band stop lower and upper pass and stop band edge frequencies.

$$F_{df}(\omega) = \sum abs[abs(|H(\omega)| - 1) - \delta_{pf}] + \sum abs[abs(|H(\omega)| - \delta_{sf})] \tag{5}$$

The first portion of Equation (5) pertains to a pass band with slice of transition band included and the last and second portions pertain to a stop band with the remaining slice of the transition band. The appropriate slice of the transition band is based on the edge frequencies of the pass band and stop band.

3. Proposed soft computing based wavelet charged system search algorithm for the digital FIR filter design

This section presents the proposed novel wavelet based charged system search (WCSS) algorithm developed to minimize the objective function as presented in Equation (5) above.

3.1. *Charged system search algorithm (CSSA) – revisited*

The charged system search algorithm as developed by Kaveh and Talatahari [11] brings about the Coulomb and Gauss laws of Physics and as well involves the laws of motion from Newton's theory. In this algorithm, charged particles act as agents and move to the search space for determining the optimal solution. The new position of a charged particle is evaluated based on the computed resultant forces or acceleration and as well the laws of motion. This section presents the fundamental pseudo-code of the charged system search algorithm [12]. The algorithm is processed in three major modules – initialization, search process and termination.

Step 1: Initialize an array of charged particles with random positions and their associated velocities are assumed to be zero.

Step 2: Compute the fitness function for the CPs. Arrange the CPs in an increasing order based on the fitness evaluated.

Step 3: A number of the first CPs and their respective fitness function values will get stored in a memory, called as charged memory (CM).

Step 4: Calculate the forces on CPs. The force vector is calculated for each CP as

$$F_j = \sum_{i,i\neq j} \left(\frac{q_i}{a^3} r_{ij}.i_1 + \frac{q_i}{r_{ij}^2}.i_2 \right) ar_{ij} p_{ij} (X_i - X_j) \times \left\langle \begin{array}{l} j = 1,2,\ldots,N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_2 = 0, i_2 = 1 \Leftrightarrow r_{ij} \geq a \end{array} \right. \quad (6)$$

where F_j is the resultant force acting on the jth CP and N is the number of CPs. The magnitude of charge for each CP (q_i) is defined considering the quality of its solution.

$$q_i = \frac{\text{fit}(i) - \text{fitworst}}{\text{fitbest} - \text{fitworst}}, \quad i = 1,2,\ldots,N \quad (7)$$

where "fitbest" and "fitworst" are the best and the worst fitness of all CPs, respectively; fit(i) represents the fitness of the agent i; and N is the total number of CPs. The separation distance r_{ij} between two charged particles is defined as follows:

$$r_{ij} = \frac{||X_i - X_j||}{||(X_i + X_j)/2 - X_{\text{best}}|| + \varepsilon} \quad (8)$$

where X_i and X_j are, respectively, the positions of the ith and jth CPs, X*best* is the position of the best current CP, and ϵ is a small positive number. Here, p_{ij} is the probability of moving each CP towards the others and the function for evaluating this is given by

$$p_{ij} = \begin{cases} 1 & \frac{\text{fit}(i) - \text{fitbest}}{\text{fit}(j) - \text{fit}(i)} > \text{rand} \vee \text{fit}(j) > \text{fit}(i) \\ 0 & \text{else} \end{cases} \quad (9)$$

In Equation (6), ar_{ij} indicates the kind of force and is given by

$$ar_{ij} = \begin{cases} +1 & \text{rand} < 0.8 \\ -1 & \text{otherwise} \end{cases} \quad (10)$$

where rand represents a random number.

Step 5: In this step, solution has to be constructed. Each CP moves to the new position and the new velocity is computed as

$$X_{j,new} = c_1.k_a.F_j + c_2.k_v.V_{j,old} + \alpha.X_{j,old} \quad (11)$$

$$V_{j,new} = X_{j,new} - X_{j,old} \quad (12)$$

In Equation (11), k_a is the acceleration coefficient; k_v is the velocity coefficient to control the influence of the previous velocity; and c_1 and c_2 are two random numbers uniformly distributed in the range (0, 1) and α is the scaling factor.

Step 6: Process of updation is now carried out. If a new CP exits from the allowable search space, then sort it increasingly to correct its position. In addition, if some new CP vectors are better than the worst ones in the CM; these are replaced by the worst ones in the CM.

Step 7: Apply termination control criterion. Perform Steps 2–6 repeatedly until termination criterion is met.

3.1.1. *Theory of wavelets*

In wavelet theory, a continuous-time function $\psi(x)$ is called as a wavelet or a mother wavelet on satisfying the below given characteristic properties:

(i) $$\int_{-\infty}^{+\infty} \psi(x)\,\mathrm{d}x = 0 \quad (13)$$

(ii) $$\int_{-\infty}^{+\infty} |\psi(x)|^2\,\mathrm{d}x < \infty \quad (14)$$

Equation (13) infers that the total positive momentum of the continuous time function is equal to that of the total negative momentum of the continuous time function. From Equation (14), it is inferred that the majority of the energy of the continuous time function is restricted to a finite duration and is bounded in nature ([13,14]). Figure 1 shows a wavelet in a specified domain.

The continuous time function with a control on magnitude is defined as follows:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right); \quad x \in \Re, a, b \in \Re, a > 0, \quad (15)$$

where "a" is the dilation or scale parameter and "b" is the translation or shift parameter. The spread of the wavelet is controlled by "a" and the control position is

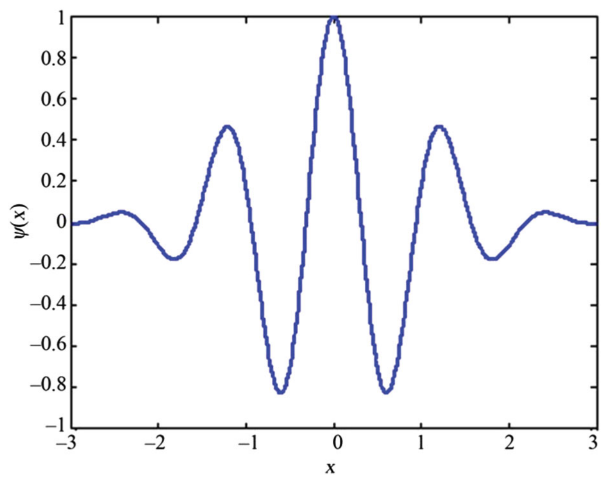

Figure 1. A type of wavelet.

determined by "b". Fundamentally, the function $\psi_{a,b}(x)$ in Equation (15) is obtained by scaling and shifting the mother wavelet. Thus, this function may be called as the daughter wavelet. The amplitude of the function in Equation (15) will be scaled down as the dilation parameter "a" increases and it is this property which is used to do the variation in the scaling factor of CSSA to enhance the searching performance. The applicability of wavelet in the proposed work is to carry out the variations in the scaling factor and this is achieved with the dilation parameter that exists in the wavelet function.

3.1.2. Applicability of wavelet with CSSA (proposed WCSS algorithm)

In case of the CSS algorithm, the charged particles will move toward the search space and perform exploration between the evaluated fitness values. Looking into the update equations (11) of position and velocity of the CSS algorithm, there exists a scaling factor "α" and it is where the wavelet function has been introduced

$$\alpha = \frac{1}{\sqrt{a}} e^{\frac{-(x/a)^2}{2}} \cos\left(5\left(\frac{x}{a}\right)\right) \tag{16}$$

where a is the dilation or scaling parameter, and translation or shifting operator b becomes equal to zero. This is the part where the WCSS algorithm is different from that of the CSS algorithm. Otherwise, all the steps for the CSS algorithm and the proposed WCSS algorithm are the same. Equation (16) represents the mother wavelet.

Hence to enhance the searching performance in the fine tuning stage, this property will be utilized in the updation operation. As over 99% of the total energy of the mother wavelet function is contained in the interval $[-2.5, 2.5]$ for the function defined in Equation (16), x can be randomly generated from $[-2.5 \times a, 2.5 \times a]$. The dilation parameter a can be set to vary with the value of n/N to meet the fine tuning needs, where n is the current iteration number and N is the maximum number of iterations. A monotonic increasing function governing a and n/N may be written as given in the following equation [14]:

$$a = e^{-\ln(g_1)\times(1-(n/N))^{\xi_{\omega m}}+\ln(g_1)} \tag{17}$$

where $\xi_{\omega m}$ is the shape parameter of the monotonic increasing function and $g_1$is the upper limit of the parameter a. The value of a is thus between 1 and g_1. The magnitude of the parameter α decreases as a increases toward $g_1$with the increase in iteration cycles; thus, performing an effective search or exploration stages and fine tuning during the local search or exploitation stage near the end of the maximum iteration cycles. Thus, a stability between the exploration of new regions and the exploitation of the already sampled regions in the search space is expected in the WCSS Algorithm and which is been achieved with the introduction of wavelets for the updation process.

4. Numerical examples and results using the proposed WCSS soft computing algorithm

The proposed WCSS algorithm is applied for the computing the optimal FIR filter coefficients for LP, HP, BP and BS filter types. The normalized filter coefficients for carrying out the simulation process are same as that are given in Table 2. The various parameters considered for the proposed WCSS algorithm are as given in Table 3.

The simulation for determining the optimal FIR filter coefficients is carried out in MATLAB R2012a environment and executed in a PC with Intel core i5 processor with 3.5 GHz speed and 10GB RAM with the 64 bit operating system. Table 4 shows the optimal FIR filter coefficients of LP, HP, BP and BS filters tuned using the proposed WCSS algorithm and is compared with that of the other evolutionary algorithms used for computing the coefficients as taken from the literature studies [15–17].

The maximum stop band attenuation of the designed LP, HP, BP and BS filters using the proposed WCSS algorithm and as well that of the other methods considered for comparison from the literature are tabulated in Table 5. The magnitude and phase response for all the designed filters using the developed WCSS algorithm is presented in Figure 2.

It is inferred from Table 5 that the developed WCSS technique achieves maximum stop band attenuation for the designed filters with respect to the other methods considered for comparison. Employing the optimal

Table 3. Proposed WCSS algorithmic parameters.

Parameters	BBO
No. of charged particles	50
Charged memory considering rate	0.95
Maximum iteration	500
Filter coefficients limits	−2 to +2
$\xi_{\omega m}$	2
g_1	10,000

Table 2. Filter coefficients for filter design (FIR).

Normalized parameters	Low pass	High pass	Normalized parameters	Band pass	Band stop
Pass band edge frequency	0.45	0.55	Lower pass band edge frequency	0.35	0.25
			Lower stop band edge frequency	0.25	0.35
Stop Band edge frequency	0.55	0.45	Upper pass band edge frequency	0.65	0.85
			Upper stop band edge frequency	0.75	0.75
Transition width	0.1	0.1	Transition width	0.1	0.1

Table 4. Optimal FIR filter coefficients for order 20 employing proposed WCSS algorithm.

h(*N*)	Optimal FIR LP filter coefficients	Optimal FIR HP filter coefficients	Optimal FIR BP filter coefficients	Optimal FIR BS filter coefficients
$h(1) = h(21)$	0.029961254364576	0.029912453654980	0.039215647023387	0.013198245346570
$h(2) = h(20)$	0.050167235143543	−0.049872125634709	−0.003349781254681	0.059843213654636
$h(3) = h(19)$	0.006932645369188	0.003412878231098	−0.081732137567469	0.019134286787622
$h(4) = h(18)$	−0.032145635682738	0.044678109213891	0.003912347657499	0.050124353453987
$h(5) = h(17)$	−0.001292435376984	0.000099832167849	0.057128319527187	−0.045113309823417
h(6) = $h(16)$	0.065123675684190	−0.059498712309432	0.001987341367398	−0.062100952364516
$h(7) = h(15)$	0.004932475756284	0.003713267091237	0.112541958342767	−0.001000492341849
$h(8) = h(14)$	−0.182356475843873	0.107839536574123	−0.005721093143788	−0.067125435128765
$h(9) = h(13)$	0.003982105541789	−0.003912872546520	−0.301982134517658	0.347091335678777
$h(10) = h(12)$	0.351989241246536	−0.351609216723199	0.003119812354176	0.075641290846939
$h(11)$	0.504923981023332	0.499981461098444	0.400369877077545	0.500000357523254

Table 5. Designed filters Stop band attenuation of order 2.

	Maximum stop band attenuation (dB)				
Filter type	PM (Park McClellan 1972) [10]	GA (Ababneh & Bataineh 2008) [15,18]	PSO (Ababneh & Bataineh 2008) [15,18]	DE (Luitel & Ganesh 2008) [17]	Proposed WCSS approach
Low pass	23.56	26.11	28.03	29.53	36.45
High pass	23.55	25.25	28.1	29.16	34.21
Band pass	22.37	30.8	32.03	32.58	35.74
Band stop	21.65	29.73	30.56	30.96	35.23

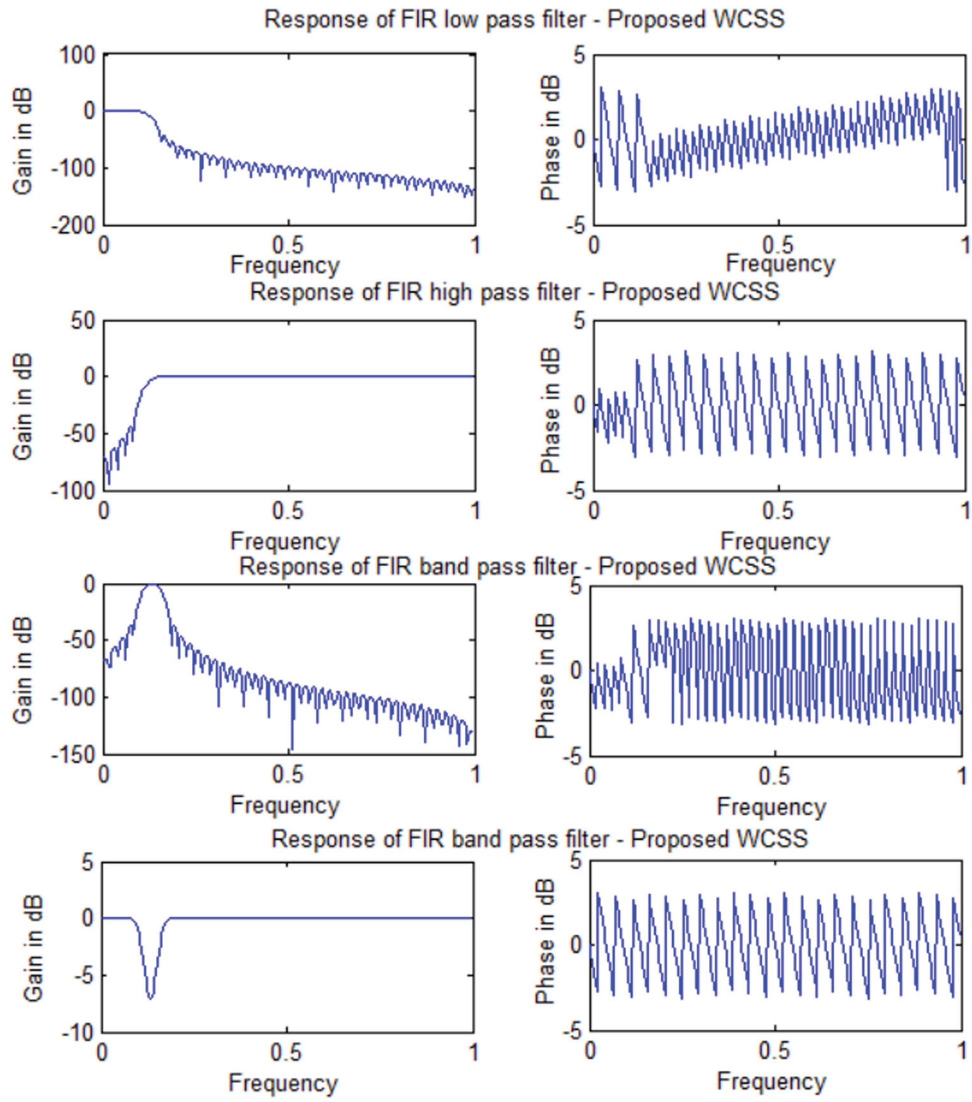

Figure 2. Magnitude and phase response using proposed WCSS.

coefficients computed using the WCSS algorithm, the plot of magnitude and phase response is computed and is as shown in Figure 2. It is well noted that the proposed WCSS technique performs in a better manner for computing the sustainable optimal filter coefficients in comparison with that of the earlier methods considered for comparison from the literature. It is inferred from Figure 2 that the respective gain values and phasor values are obtained for the specified values of the order of filters.

5. Simulation results, discussions and comparative analysis of the proposed algorithms

The proposed WCSS algorithm is applied to compute the sustainable optimal FIR filter coefficients and the numerical solutions obtained for each of the. Execution times taken for the completion of the specified cycles for the proposed soft computing based WCSS algorithm are the lowest in comparison with that of the other methods, and are as tabulated in Table 6.

Table 6. Comparative statistical analysis of sustainable FIR filter design of all algorithms.

Considered algorithms for comparison	For stop band ripple (normalized) Maximum	Minimum	Average	Variance	Standard Deviation	Execution time for 100 cycles (s)
		FIR low pass filter of order 20				
Parks–McClellan algorithm [10]	0.06636	0.06464	0.065986	4.54 e^{-7}	0.000673	-
Genetic algorithm [15]	0.04949	0.01196	0.025522	0.000197	0.014026	5.7174
Particle swarm Optimization [15]	0.03967	0.01089	0.018986	0.000121	0.010983	3.3286
differential evolution [17]	0.03339	0.009651	0.01609	7.51 e^{-5}	0.008666	3.9543
Proposed WCSS	0.01908	0.01001	0.01327	6.0 e^{-6}	0.002134	2.9915
		FIR high pass filter of order 20				
Parks–McClellan algorithm [10]	0.06645	0.06622	0.06637	6.32 e^{-9}	7.95 e^{-5}	-
Genetic algorithm [15]	0.05461	0.01405	0.028603	0.000254	0.015925	5.3667
Particle swarm optimization [15]	0.03935	0.01125	0.01916	0.000111	0.010525	3.0435
Differential evolution [17]	0.03483	0.008113	0.016107	9.19 e^{-5}	0.009585	3.9374
Proposed WCSS	0.01932	0.00953	0.01507	1.00 e^{-6}	0.002843	2.0951
		FIR band pass filter of order 20				
Parks–McClellan algorithm [10]	0.07609	0.07404	0.075675	5.37325 e^{-7}	0.0007333	-
Genetic algorithm [15]	0.02885	0.01098	0.016855	3.58388 e^{-5}	0.005987	6.3827
Particle swarm optimization [15]	0.02504	0.01025	0.0158933	3.89082 e^{-5}	0.006238	4.6850
Differential evolution [17]	0.0235	0.01028	0.015125	2.56911 e^{-5}	0.005069	4.9832
Proposed WCSS	0.01683	0.01017	0.01321	3.0 e^{-6}	0.002214	3.8451
		FIR band stop filter of order 20				
Parks–McClellan algorithm [10]	0.08273	0.08228	0.082543	3.66889 e^{-8}	0.000192	-
Genetic algorithm [15]	0.03262	0.01656	0.023198	3.12609 e^{-5}	0.005591	6.2846
particle swarm optimization [15]	0.02966	0.01565	0.020872	2.9462 e^{-5}	0.005428	4.8777
Differential evolution [17]	0.02832	0.01431	0.021562	2.42038 e^{-5}	0.004920	5.0005
Proposed WCSS	0.02047	0.01287	0.016873	1.75 e^{-5}	0.003927	4.0003

Table 7. Other Comparative statistical analysis of sustainable FIR filter design of all algorithms.

Considered algorithms for comparison	For pass band ripple (normalized) Maximum	Minimum	Mean	Variance	Standard deviation
		FIR low pass filter of order 20			
Genetic algorithm [15]	0.114	0.112	0.113	0.000001	0.001
Particle swarm optimization [15]	0.123	0.116	0.1193	8.223×10^{-6}	0.00287
differential evolution [17]	0.135	0.113	0.124	0.000121	0.011
Proposed WCSS	0.097	0.091	0.1003	2.198×10^{-4}	0.00090
		FIR high pass filter of order 20			
Genetic algorithm [15]	0.117	0.109	0.113	0.000016	0.004
Particle swarm optimization [15]	0.122	0.111	0.118	2.467×10^{-5}	4.966×10^{-3}
Differential evolution [17]	0.136	0.108	0.125	1.487×10^{-4}	1.219×10^{-2}
Proposed WCSS	0.102	0.095	0.091	9.2×10^{-6}	9.12×10^{-4}
		FIR band pass filter of order 20			
Genetic algorithm [15]	0.167	0.152	0.1595	5.625×10^{-5}	0.0075
Particle swarm optimization [15]	0.146	0.143	0.1445	2.25×10^{-6}	0.0015
Differential evolution [17]	0.152	0.147	0.1495	6.25×10^{-6}	0.0025
Proposed WCSS	0.124	0.128	0.1396	1.74×10^{-6}	0.001
		FIR band stop filter of order 20			
Genetic algorithm [15]	0.117	0.11	0.1136	8.227×10^{-6}	2.875×10^{-3}
Particle swarm optimization [15]	0.125	0.098	0.1117	1.216×10^{-4}	0.0112058
Differential evolution [17]	0.115	0.108	0.111	8.667×10^{-6}	2.944×10^{-3}
Proposed WCSS	0.101	0.071	0.1062	7.46×10^{-6}	0.000109

Table 8. Objective function values.

Type of the filter (with order 20)	Algorithms compared	Iteration cycles	Objective function value (error)
FIR low pass	Genetic algorithm [15]	367	5.6743
	Particle swarm optimization [15]	424	3.9871
	Differential evolution [17]	396	1.7865
	Proposed WCSS	234	1.5067
FIR high pass	Genetic algorithm [15]	346	4.088
	Particle swarm optimization [15]	482	2.584
	Differential evolution [17]	431	1.816
	Proposed WCSS	210	1.001
FIR band pass	Genetic algorithm [15]	329	4.5632
	Particle swarm optimization [15]	436	3.7621
	Differential evolution [17]	467	3.0176
	Proposed WCSS	236	1.3987
FIR band stop	Genetic algorithm [15]	398	5.0731
	Particle Swarm optimization [15]	429	4.5694
	Differential evolution [17]	401	3.9831
	Proposed WCSS	229	1.6129

Table 6 tabulates the details of the statistical analysis of the execution process which includes the parameters – maximum, minimum, mean, variance and standard deviation of the stop band ripple along with the execution time taken to achieve the least fitness value. It is noticed that the proposed WCSS algorithm results in the lowest stop band ripples among all the algorithms considered for all types of filters. Similarly, the WCSS algorithm based average and variance of stop band ripples are comparatively lower than the other considered algorithms [10, 15,17]. These values are lower than the comparative algorithms considered for comparison.

The maximum, minimum, average, variance and standard deviation of pass band ripple for the proposed algorithms and that of the algorithms considered for comparison [10,15,[17] are evaluated and summarized as shown in Table 7. From Table 7, it is noted that in this case proposed WCSS algorithm results in better solution and yields lower average and variance values in comparison with that of the other methods. The stability of performance in the stop band region is found to be maintained for all cases. On obtaining the response plots individually for all the considered algorithms for comparison, the proposed WCSS algorithmic response reduces the fitness error to a minimal value than the existing methods. Henceforth, it is noted that the proposed WCSS algorithm converges to a lower error fitness value in comparison with that of GA, PSO, DE approaches. Table 8 shows the tabulation of the fitness value converged for the proposed algorithm and that of the existing algorithms. For all filter types, the proposed WCSS algorithm converges to the minimum error fitness values for computing the optimal filter coefficients.

From Table 8 and Figure 3 (shows for FIR HP filter) it is well observed that the proposed WCSS algorithm gets converged with minimal error fitness value than that of the existing methods considered from the literature [19–21]. Hence for all the filter types, the modelled WCSS algorithm better converges with minimal execution times and to that of the least minimum error

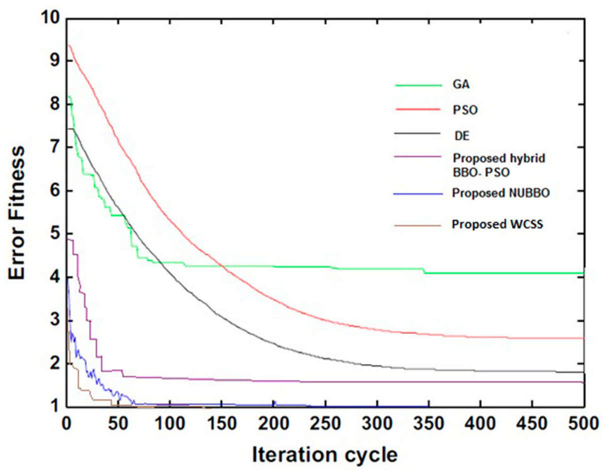

Figure 3. Plot for convergence of objective function value with iterations.

fitness values. The convergence is attained at a faster rate employing the proposed algorithm, and this is due to the positional and velocity updates of the charged particles. The update of charged particles tends to move towards an optimal solution due to the inclusion of the dilation parameter for varying the scaling factors. The developed approach can be employed and designed for filters of higher order as well.

6. Summary

In this paper, a wavelet based operation is carried out for enhancing the scaling factor involved in the updation equation of the basic charged system search algorithm. The specified scaling factor is modified using the dilation and transition parameters of wavelets which improve the exploration rate of the charged system search algorithm and this introduction of wavelet theory in CSS has resulted in the proposed wavelet CSS algorithm. The algorithm developed is applied to design the optimal FIR filter coefficients of all types and the results computed are compared with the existing methods from the literature. On analysing the results, it is inferred that the proposed WCSS algorithm outperforms all the other algorithms used for the purpose increasing the stop band attenuation, minimizing the execution time, decreasing pass band ripple and stop band ripple as well reducing the error fitness function, so that it converges faster. As a result, the developed WCSS algorithm in this paper is proved to be a best global optimizer for computing the optimal filter coefficients to design practical digital FIR filters for digital signal processing applications.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

S. N. Deepa http://orcid.org/0000-0003-2150-5051

References

[1] Fang W, Sun J, Xu W, et al. FIR digital filters design based on quantum-behaved particle swarm optimization. First International Conference on Innovative Computing, Information and Control, ICICIC '06, vol. 1; 2006; Beijing, China. p. 615–619.
[2] Teixeira F, Romariz A. Optimum finite impulse response digital filter design using computational intelligence based optimization algorithms. Seventh International Conference on Intelligent Systems Design and Applications, 2007. ISDA 2007. IEEE, 2007; Brazil. p. 635–640.
[3] Najjarzadeh M, Ayatollahi A. FIR digital filters design: particle swarm optimization utilizing LMS and minimax strategies. IEEE International Symposium on Signal Processing and Information Technology, ISSPIT 2008; 2008; Bosnia and Herzegovina. p. 129–132.
[4] Karaboga N. A new design method based on artificial bee colony algorithm for digital IIR filters. J Franklin Inst. 2009;346(4):328–348.
[5] Kar R, Mandal D, Bardhan S, et al. Optimization of linear phase FIR band pass filter using particle swarm optimization with constriction factor and inertia weight approach. 2011 IEEE Symposium on Industrial Electronics and Applications (ISIEA), IEEE, 2011; Langkawi, Malaysia. p. 326–331.
[6] Ghosh A, Ghosh A, Chowdhury A, et al. Linear phase low pass FIR filter design using genetic particle swarm optimization with dynamically varying neighbourhood technique. 2012 IEEE Congress on Evolutionary Computation (CEC). IEEE, 2012; Brisbane, QLD, Australia. p. 1–7.
[7] Mondal S, Ghoshal SP, Kar R, et al. Novel particle swarm optimization for low pass fir filter design. 2012 IEEE Symposium on Humanities, Science and Engineering Research (SHUSER*)*, 2012; Kuala Lumpur. p. 24–27.
[8] Saha SK, Ghoshal SP, Kar R, et al. Cat Swarm optimization algorithm for optimal linear phase FIR filter design. ISA Trans. 2013;52:781–794.
[9] Oppenheim AV, Schafer RW, Buck JR. Discrete-Time signal processing. Englewood Cliffs (NJ): Prentice Hall; 1999.
[10] Parks TW, McClellan JH. Chebyshev approximation for non recursive digital filters with linear phase. IEEE Trans Circuit Theory. 1972;19:189–194.
[11] Kaveh A, Talatahari S. A novel heuristic optimization method: charged system search. Acta Mech. 2010;213(3-4):267–289.
[12] Kaveh A, Talatahari S. Hybrid charged system search and particle swarm optimization for engineering design problems. Eng Comput (Swansea). 2011;28(4): 423–440.
[13] Ling SH, Iu HHC, Leung FHF, et al. Improved hybrid particle swarm optimized wavelet neural network for modelling the development of fluid dispensing for electronic packaging. IEEE Trans Ind Electron. 2008;55(9):3447–3460.
[14] Daubechies I. The wavelet transform, time frequency localization and signal analysis. IEEE Trans Inf Theory. 1990;36(5):961–1005.
[15] Ababneh JI, Bataineh MH. Linear phase FIR filter design using particle swarm optimization and genetic algorithms. Digit Signal Process. 2008;18(4): 657–668.
[16] Karaboga N, Cetinkaya B. Design of digital FIR filters using differential evolution algorithm. Circuits Syst Signal Proc. 2006;25(5):649–660.
[17] Luitel B, Venayagamoorthy GK. Differential evolution particle swarm optimization for digital filter design. IEEE Congress on Evolutionary Computation, CEC 2008; 2008; Hong Kong, China. p. 3954–3961.
[18] Ahmad SU, Antoniou A. A genetic algorithm approach for fractional delay FIR filters. IEEE International Symposium on Circuits and Systems, ISCAS 2006; 2006; Kos, Greece. p. 2517–2520.
[19] Kaveh A, Talatahari S. Optimal design of skeletal structures via the charged system search algorithm. Struct Multidiscipl Optim. 2010;41(6):893–911.
[20] Özyön S, Temurtaş H, Durmuş B, et al. Charged system search algorithm for emission constrained economic power dispatch problem. Energy. 2012;46(1):420–430.
[21] Precup RE, David RC, Petriu EM, et al. Novel adaptive charged system search algorithm for optimal tuning of fuzzy controllers. Expert Syst Appl. 2014;41(4):1168–1175.