Studies on Design of Band-pass Filter using Quantum Inspired Sine Cosine Algorithm

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ABSTRACT

This thesis presents optimal design of Type-1 digital FIR band-pass filters using population based meta-heuristic optimization algorithms. A recently developed evolutionary optimization method, Sine Cosine Algorithm (SCA) is discussed in this thesis. A novel algorithm based on SCA, named as Quantum inspired Sine Cosine Algorithm (QSCA) is proposed in this work. This newly proposed algorithm has also been used in this thesis for the optimal design of FIR band-pass filters. To demonstrate the efficacy of the proposed method, the filter design has been simulated in MATLAB. Further, to show the comparative effectiveness of the proposed algorithm, the simulation results have been compared with the results of the already existing well established algorithms such as Parks McClellan (PM) algorithm and SCA.

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Chapter 1

Introduction

1.1 Preamble

We use various kinds of filters in our homes, offices, and schools like water filter, air filter etc.. This highlights the fact that filters are very important in our lives to sustain a good standard of living. Similarly, in the field of electronics too filters are very essential elements. The term 'filtering' usually refers to the quality or process of blocking something out while allowing some other things to pass through. Electronic filters refer to the devices that upon receiving input signals, allow only the components within a certain range of frequencies to transmit and attenuate the rest of the components outside that frequency range. Electronic filters have been categorized in the literature based upon various criteria. Depending upon the type of components used in construction, filters are classified as— active and passive. Based upon operating frequency ranges filters may be classified as Audio Frequency (AF) or Radio Frequency (RF). According to the nature of impulse response, filters can be categorized as— Finite Impulse Response (FIR) or Infinite Impulse Response (IIR). As opposed to IIR filters, FIR filters are non-recursive and the response due to impulse input settles down to zero in a finite amount of time. FIR filters are preferred over IIR filters in a wide array of engineering applications because of the linear phase and greater stability offered by the former [1-2]. Again, depending on the nature of filtering operation, filters can be classified as— analogue and digital. Digital filter circuits have to sample the analogue input signal, convert the sampled signal into a set of binary numbers, store the numbers in a memory, and process them through a processing unit before digitally manipulating them to yield the final output [3-5]. None of these steps are required in an analogue filter. Despite the higher complexities of digital filters, they are more widely preferred over analogue filters these days because of the numerous advantages it offers like linear phase response, adaptability, repeatability, data storage ability etc..

Section 1.2 of this chapter presents literature survey in the field of optimization techniques. Section 1.3 reveals the motivation behind taking up this work. The thesis outline is presented in Section 1.4 and finally this chapter is summarized in Section 1.5.

1.2 Literature Survey

The primary objective of using meta-heuristic optimization algorithms for digital filter design is to reduce the error between the ideal response and the approximated response (cost function) as much as possible. Development of meta-heuristic algorithm has eliminated the requirements of the conventional gradient-based design processes like continuous and differentiable cost function. In addition to this, these algorithms have much lesser probability of getting trapped in local minima, which is popularly known as "Local optima entrapment" problem. Algorithms like, Simulated Annealing [6-7], Genetic Algorithm [8-9], Artificial Bee Colony [10-12], Particle Swarm Optimization [13-17], Cuckoo Search [18-21], Gravitational Search [22-24], etc. are significant innovations in optimization paradigm.

According to No Free Lunch theorem [25], there can be no single universal method that can provide solutions to all the applications requiring optimization. This theorem logically proves that any one algorithm can only successfully solve a specific set of problems. This compels researchers to design and develop newer or modified algorithms to obtain better performing results in solving diverse set of problems. In 2016, a new algorithm named as Sine Cosine Algorithm (SCA) [26-27], was developed for solving optimization problems. This algorithm mainly depends on the periodic property of sinusoidal functions to achieve exploration and exploitation within the search region. This has wide range of applications in various real life design optimization problems like in obtaining the optimal shape of an aircraft's wings. Based on this algorithm, various other improved algorithms have come up in the last few years. A few examples of these are Opposition based Sine Cosine Algorithm (OSCA) [28-29], Weighted Update Position Mechanism based SCA (WUPM-SCA) [30], Multi-Orthogonal Sine Cosine Algorithm (MOSCA) [31], Improved Sine Cosine Algorithm (ISCA) with crossover scheme [32]. OSCA relies on opposition technique to improve the exploration in the search region and finds its application in training feed forward neural networks. WUPM-SCA is an improved version of SCA. In WUPM-SCA weights are assigned to the search agents based on their fitness values and these search agents are utilized to update the positions of the population until they converge to global optima.

Besides, different algorithms have been hybridized with SCA in order to combine the strengths of two different algorithms and eliminate their weaknesses as much as possible. Examples of these are Grey-Wolf Optimizer with SCA [33], SCA with Particle Swarm Optimization [34], and SCA with Differential Evolution [35]. All of these algorithms find applications in engineering design problems. Most of these algorithms may not provide accurate results but give approximate and quite satisfactory solutions.

1.3 Thesis Motivation

Digital FIR BP filters have never been designed using Sine Cosine Algorithm (SCA), a newly developed population based optimization algorithm. The fact that no such endeavor to design FIR BP filters using SCA had been taken up before, itself was a motivating factor at the outset and provided with a challenge before us to take up the task and be successful at it. As we proceeded along with the work of simulating the design of FIR filters on MATLAB utilizing SCA, we observed that the performance of the algorithm was at best, satisfactory for lower orders of filter and just simply bad for higher orders. The output filter response would have high amount of ripples in the pass-band and lower attenuation in the stop-band. This deemed the algorithm unsuitable for efficient design of FIR filters. This provided us with a second dose of motivation to improve upon the performance of SCA in terms of FIR filter design. In order to achieve this goal, a novel algorithm based on SCA and inspired by the laws of Quantum mechanics [36-37], was proposed and developed further. In this paper, this newly proposed algorithm has been discussed. It is also shown with supporting data and figures that FIR filters can be designed in an efficient and fast manner using the new algorithm.

1.4 Thesis Outline

The thesis has been systematically organized and efforts have been taken to cover the theoretical aspects in detail about the practical work performed in the laboratory. This thesis is about the design of FIR band-pass filters using fast and efficient optimization techniques.

Chapter 1 gives the introduction which basically talks about the importance of filtering, classification of electronic filters, as well as advantages of FIR and digital filters over IIR and analogue filters respectively. Apart from this, a literature survey regarding optimization algorithms, motivation behind the current work, and finally the thesis outline is provided in this chapter.

Chapter 2presents the theoretical details along with a pseudo-code and a flowchart of a fairly new optimization algorithm, known as Sine Cosine Algorithm (SCA). A new algorithm based on SCA, named as Quantum inspired Sine Cosine Algorithm (QSCA) have also been proposed and discussed in the chapter in detail.

Chapter 3 is about the application of the newly proposed algorithm for the purpose of designing FIR band-pass filters. Problem formulation FIR BP filters is provided in the starting of the chapter. In the later part of the chapter, the performance of QSCA in the context of FIR filter design has been demonstrated and analyzed in comparison to other existing algorithms such as Parks McClellan (PM) and SCA. Relevant figures and data in tabulated form have been provided to support the discussion.

Chapter 4 gives the final conclusion of the complete thesis work.The future scope in the domain of filter design utilizing optimization algorithmsis also discussed in this chapter.

Chapter 2

Design Methodologies:
Optimization Algorithms

2.1 Introduction

Finite Impulse Response (FIR) filters are a category of filters, the impulse response of which becomes zero in finite duration of time. An FIR filter structure can be used to digitally implement almost any kind of filter response. An FIR filter circuit usually consists of a series of delays, adders, and multipliers. Other popular terms for FIR filters are "'Feed-forward', 'Non-recursive', or 'transversal' filter. Whereas, Band-pass (BP) filters are another category of filters which allow only the components within a certain frequency range to pass through and attenuate the rest of the components outside that frequency range. An ideal band-pass filter response would have an absolutely smooth and flat pass-band without any ripple, and there would be complete rejection of all the components in the stop-band. Moreover, the switching between stop-band and pass-band would be instantaneous i.e., the transition width would be zero.

The term 'optimization' refers to the process of selecting the best option from a set of other alternative options. An optimization problem generally consists of inputs which can be stored as variables, one or more objective or cost function which is evaluated for each input, and the output of this objective function is known as the fitness or cost of the solution. Objective functions are also termed as 'fitness functions'. In the simplest case, optimization problems are about finding the highest or least value of some function with some constraining conditions. This chapter mainly deals with the topic of design methodologies of digital filters in the form of meta-heuristic optimization techniques. Population based evolutionary optimization methods are highly preferred over the traditional methods for solving complicated real world problemssimply because of the advantages offered by them like non-requirement of continuous and differentiable cost functions and the much lesser probability of getting stuck in a local optima without ever reaching the global optima. Two such optimization methods are presented in the following sections.

Section 2.2 of this chapter presents an extensive description of Sine Cosine Algorithm (SCA). In section 2.3, a new and better version of SCA named as Quantum Inspired Sine Cosine Algorithm (QSCA) has been proposed. The pseudo code and flowchart of the algorithm have been given in the same section.

2.2 Sine Cosine Algorithm (SCA)

In general, all population based optimization algorithms have some common framework. They all start with randomly generating initial solutions also called as search agents. Then the fitness value of each solution is determined using objective function specific to the problem. This process continues repeatedly over the iterations until a desired optimum solution is reached. All of the meta-heuristic optimization techniques have two broad phases—exploration and exploitation. In the former, random sets of solutions are imparted a large degree of volatility to zero in on potential regions in the solution space. Whereas, in the latter phase, the degree of randomness in position updates are reduced which results in exploiting the promising regions in a precise manner. A balanced approach between exploration and exploitation in an algorithm generally helps to reach the global solution in lesser number of iterations.

SCA is a population based optimization algorithm, developed recently. This algorithm also works within the aforementioned framework. It basically relies on the cyclic property of the sinusoidal functions to iteratively update the positions of the population agents, which helps in exploration and exploitation of the searching agents. Here, position updates of the search agents are governed by the equations:

$$X_{i,jnew}^{t} = X_{i,j}^{t} + r_1 \times \sin(r_2) \times | r_3 P_j^t - X_{i,j}^{t} | \tag{2.1}$$

$$X_{i,jnew}^{t} = X_{i,j}^{t} + r_1 \times \cos(r_2) \times | r_3 P_j^t - X_{i,j}^{t} | \tag{2.2}$$

where $X_{i,j}$ is the position of the i^{th} search agent in j^{th} dimension, $\mathrm{r}_2, \mathrm{r}_3 \in [0,1]$ and P_j is the position of the best solution in j^{th} dimension. Eq. (2.1), (2.2) are written in a compact form as follows:

$$X_{i,jnew}^{t} = \begin{cases} X_{i,j}^{t} + r_1 \times \sin(r_2) \times | r_3 P_j^t - X_{i,j}^{t} |, r_4 < 0.5 \\ X_{i,j}^{t} + r_1 \times \cos(r_2) \times | r_3 P_j^t - X_{i,j}^{t} |, r_4 \geq 0.5 \end{cases} \tag{2.3}$$

where $r_4 \in [0,1]$. The selection of r_1 decides the direction of movement of X_i^t; r_2 governs the displacement and defines how much the search agent should move towards or away from the destination position. The parameter r_3 randomly emphasizes or deemphasizes the effect of the global best position obtained so far to achieve the distance. The parameter r_4 in Eq. (2.3) is responsible for transitioning between the sine and cosine functions.

To perform exploration and exploitation in standard SCA algorithm, the value of r_1 in Eq. (2.3) are updated as:

$$r_1 = \alpha - t \cdot \left(\frac{\alpha}{T} \right) \tag{2.4}$$

where $'T'$, $'t'$, denote the maximum number and current iterations and $'\alpha'$ is a non-negative constant.

Due to the use of sinusoidal functions in population updating, this algorithm is named as Sine Cosine Algorithm (SCA). The impact of Sine and Cosine on Eqs. (2.1) and (2.2) are illustrated in Fig. 2.1. This figure shows that how the proposed equations define a space between two solutions in the search space. It should be noted that this equation can be extended to higher dimensions although a two- dimensional model is shown in Fig. 2.1. The periodic property of sine and cosine function allows a solution to be re-positioned around another solution. This feature ensures exploitation of the region defined between two solutions. For the purpose of exploration, the solutions should have the ability to search beyond the space between their corresponding global best positions as well. Changing the range of the sine and cosine functions is a step towards achieving this goal.

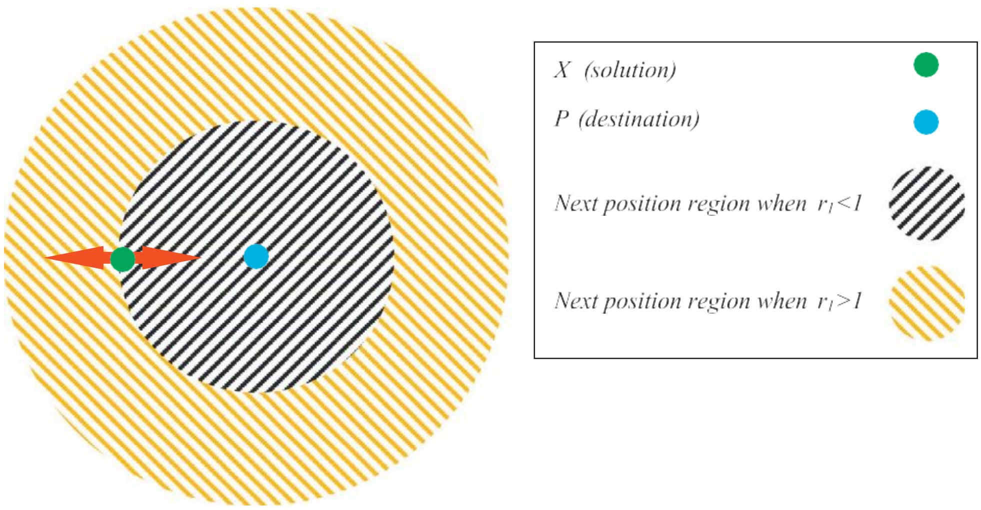

Fig 2.1 Effects of Sine and Cosine inEq. (2.1) and (2.2) on the next position

2.2.1 Pseudo-Code of SCA

Initialize *the population agents with random values*

Initialize *the values of* r_1, r_2, r_3, *and* r_4

Do

  Evaluate *the cost function for each solution*

  Find out *the best solution (i.e., which gives minimum value of the cost function)*

While (t < maximum iterations)

  Update *the value of* r_1 *through Eq. (2.4)*

  Update *the values of* r_2, r_3, *and* r_4

  Update *the solutions through Eq. (2.3)*

Returnthe optimum (best) solution obtained

This pseudo-code shows that in the starting, the SCA algorithm initializes the population by random values. The algorithm then stores the solutions with the highest fitness up to the current iteration, assigns it as the current global best solution, and updates other solutions with respect to it. Meanwhile, the ranges of the sinusoidal functions are altered to emphasize exploitation of the search region as the number of iteration increases. The SCA algorithm ends the optimization process when the number of iterations becomes higher than the predefined maximum number of iterations. Besides this other termination conditions like the accuracy of the global optimum obtained or the maximum number of function evaluation can be considered.

2.2.2 Flowchart of SCA

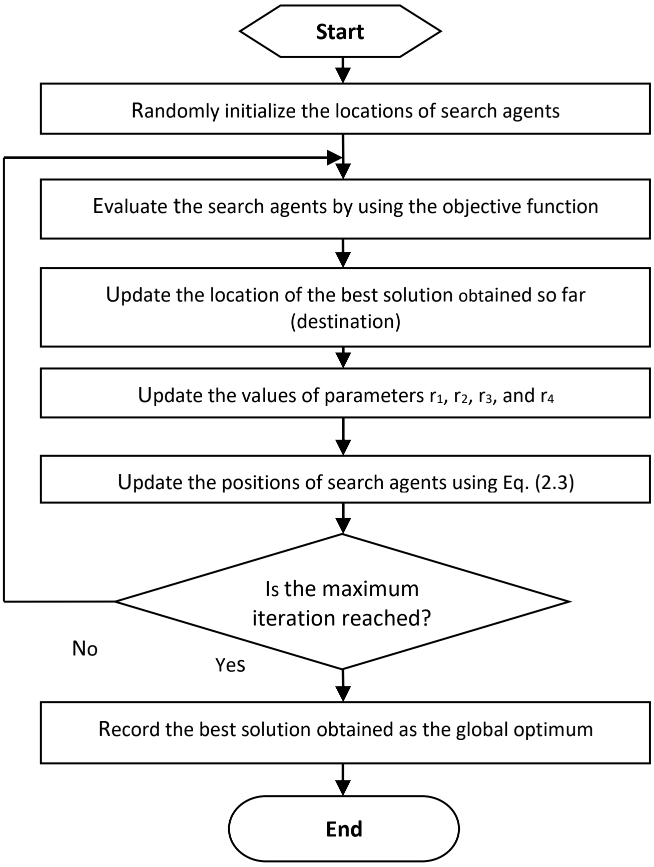

Fig 2.2 Flowchart of SCA

2.3 Quantum Inspired Sine Cosine Algorithm (QSCA)

Although the SCA can provide good accuracy in comparison with some other existing algorithms, it still has some limitations like getting trapped in some locally optimal solutions or less adequate convergence speed and accuracy. Moreover, it is not suitable for highly complex applications. This provides with ample scope for developing newer techniques that improves upon the performance of SCA. To sufficiently overcome these limitations, a new variant of SCA inspired by the laws of quantum mechanics has been proposed here. In quantum mechanics, a particle is represented by a wave function $\psi(x,t)$ instead of its exact position and velocity, as the exact values of both of these parameters cannot be known according to Heisenberg's Uncertainty Principle. In QSCA, each particle or population agent has certain uncertainty and hence behaves as if they were quantum particles. Thus the algorithm is aptly named as 'Quantum inspired Sine Cosine Algorithm'.

QSCA is superior to the classical SCA because of the following major reasons:

a) QSCA has more number of states owing to state superposition, which arises due to the quantum nature of the population agents

b) QSCA associates a degree of uncertainty with each solution such that it can be present anywhere in the search space as opposed to the finite bound in search space imposed on the solutions in classical SCA. This directly influences and improves the exploration capability of the algorithm and hence significantly reduces the chance of local optima entrapment.

With QSCA, the objectives of FIR filter design are met more accurately and the convergence is also faster compared to SCA. The dynamic behaviour of the quantum inspired population is due to the association of each particle or solution with a probability of existence through its probability density function $|\psi(x,t)|^2$. In QSCA, each solution has a position vector x_i and the population has a global best position $gbest$, which has the lowest value of the cost function in the population.

The individual solutions in the search region update their positions through the following equation:

$$X_{i,jnew}^{t} = \begin{cases} local\_p_{i,j}^{t} + c \cdot \sin(2 \cdot \pi \cdot rand) \cdot | m\_pos_j^t - X_{i,j}^{t} | \cdot \ln(1/u), rand < 0.5 \\ local\_p_{i,j}^{t} + c \cdot \cos(2 \cdot \pi \cdot rand) \cdot | m\_pos_j^t - X_{i,j}^{t} | \cdot \ln(1/u), rand \geq 0.5 \end{cases} \quad (2.5)$$

where $local\_p_{i,j}^{t} = f_{i,j} \cdot X_{i,j}^{t} + (1 - f_{i,j}) \cdot gbest_j^t$ (2.6)

The above equation describes the "Local attractor" [16], which is actually the weighted combination of the current position of a particle and the global best position of the population.

$gbest_j^t$ = global best position of the swarm at j th dimension after iteration "t";

$f_{i,j} = rand$ and $u = rand$ are random numbers,

$$m\_pos_j^t = \frac{1}{N} \sum_{i=1}^{N} X_{i,j}^{t}; \; j = 1,2,...,d \quad (2.7)$$

is the d- dimensional vector describing the average position of all the particles at iteration "t", and

$$c = a \cdot e^{-\left(\frac{t}{T}\right)} \quad (2.8)$$

Is the exponentially decreasing “exploration-exploitation coefficient”, where a= constant, t= current iteration and T= maximum number of iteration.

2.3.1 Pseudo-Code of QSCA

Initialize *the population agents with random values*

Do

Evaluate *the cost function for each solution*

Find out *the global best solution, gbest*

While (t < maximum iterations)

Update *the value of c through Eq. (2.8)*

Evaluate *the m_pos of all the particles through Eq. (2.7)*

Find out *the value of local attractor, local_p through Eq. (2.6)*

Update *the positions of the particles through Eq. (2.5)*

Return the optimum (best) solution obtained

The algorithm starts by initializing the population with randomized values. The cost function is evaluated for the solutions in the search space and the solution with the lowest value of cost function is found, which the global best solution. The value of the exploration-exploitation coefficient, c is updated through Eq. (2.8). The average of all the particle positions (m_pos) is evaluated. The value of local attractor (local_p), which is a weighted combination of the current position of a particle and the global best position of the swarm, is determined by Eq. (2.6). Lastly, the particle positions are updated through the Eq. (2.5). The above processes continue until the maximum iteration is reached or some other end criterion is satisfied. At the end, the optimum solution is returned.

2.3.2 Flowchart of QSCA

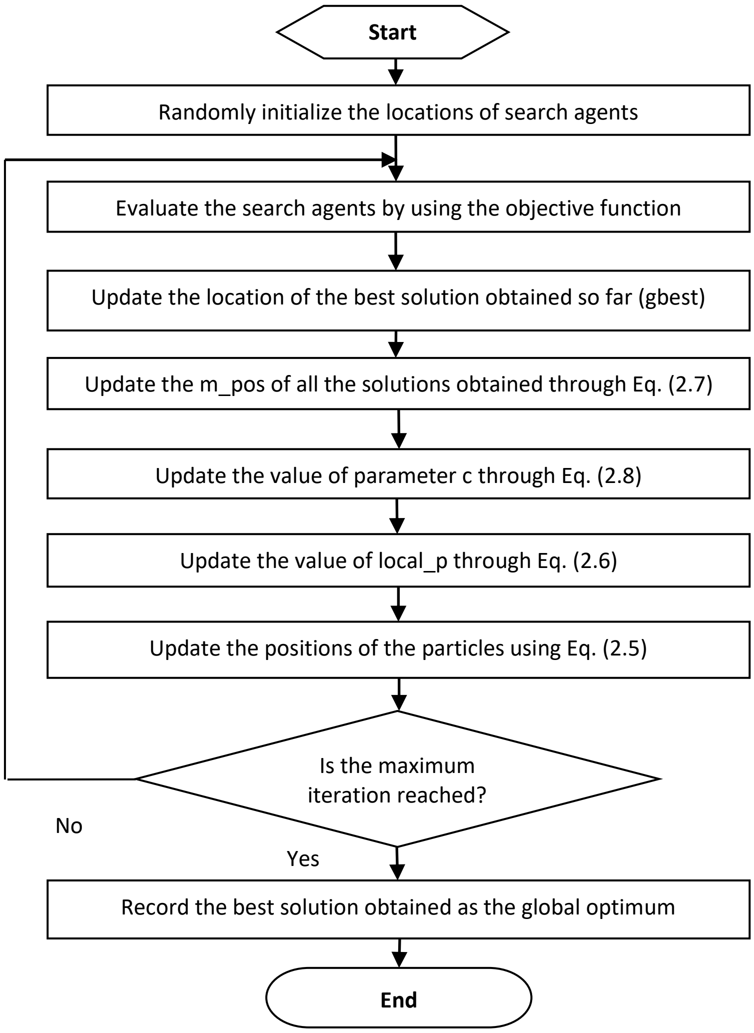

Fig 2.3 Flowchart of QSCA

Band-pass FIR filters can be efficiently designed with the help of this novel algorithm, as the filter response has been simulated in MATLAB and we have obtained better outcome in all the cases in comparison with SCA. The simulation results and analysis are presented in the next chapter.

2.4 Summary

This chapter starts with brief descriptions of FIR and BP filters. Then the chapter proceeds with a sufficiently detailed presentation of the design methodologies of FIR filters in the form of evolutionary optimization algorithms such as Sine Cosine Algorithm (SCA). After that, in the following section a better version of the classical SCA is proposed and the major reasons behind its superiority over SCA have been discussed in the section.

Chapter 3

Simulation Results and Analysis of FIR filter design using QSCA

3.1 Introduction

This chapter presents the problem formulation of Type-1 band-pass FIR filter. Simulation results and analysis of designing FIR filter QSCA are provided in the later part of the chapter. QSCA is a better and faster version of Sine Cosine Algorithm (SCA). SCA is a simple, population based robust evolutionary algorithm but has the problem of sub-optimality. QSCA has overcome the above disadvantage faced by SCA. The simulation results show that QSCA outperforms SCA not only in terms of magnitude response but also in terms of convergence speed and thus proves itself to be a promising candidate for FIR filter design.

Section 3.2 provides the problem formulation for BP FIR filter and the simulation results along with analysis are presented in the section 3.3 of this chapter.

3.2 Problem Formulation for Band-Pass FIR Filter

The system function of FIR filter is represented by [3]:

$$H(z) = \sum_{n=0}^{M-1} h(n) z^{-n} \quad n = 0,1,\ldots,M-1 \tag{3.1}$$

which consists of $(M-1)$ poles at origin and $(M-1)$ zeroes. Based on the coefficients of $h(n)$ a filter can exhibit different type of magnitude responses.

3.2.1 Error Function Representation

In reality, by changing degrees of favourable outcomes and minimizing the deviation of the designed magnitude response from the ideal, the desired filter is achieved. The weighted difference in stop-band and pass-band primarily defines the error function as given in [3]:

$$E(\omega) = W(\omega)\left[\, H_d\left(e^{j\omega}\right) - H_a\left(e^{j\omega}\right)\,\right] \tag{3.2}$$

The error function $E(\omega)$, given by Parks-McClellan (PM) is represented in Eq. (3.2), where $W(\omega)$, $H_d\left(e^{j\omega}\right)$, $H_a\left(e^{j\omega}\right)$ are the weight vector, desired, and approximated frequency response respectively. Weight function $W(\omega)$ modulates the minimization of error.

In error function $E(\omega)$, the ratio between peak ripple at pass-band (δ_p) and stop-band (δ_s) cannot take different values. Thus, in order to overcome the flaws in this function, a modified error function is used [3]:

$$U = \max_{\omega \le \omega_p}\left(\left|E(\omega)\right| - \delta_p\right) + \max_{\omega \ge \omega_s}\left(\left|E(\omega)\right| - \delta_s\right) \tag{3.3}$$

where ω_p , ω_s , δ_p and δ_s are the desired filter specifications.

3.2.2 Ideal Response of Band-Pass Filter

The band-pass filter's ideal response can be denoted by [3]:

$$H_d\left(e^{j\omega}\right) \begin{array}{ll} =0 & 0 \le \omega \le \omega_{s1} \\ =1 & \omega_{p1} \le \omega \le \omega_{p2} \\ =0 & \omega \ge \omega_{s2} \end{array} \tag{3.4}$$

where ω_{s1}, ω_{s2} represent the first and the second stop-band frequencies of band-pass FIR filter. Similarly, ω_{p1} and ω_{p2} are the first and the second pass-band frequency.

3.2.3 Type-1 Linear Phase FIR Filter

The frequency response function of FIR filter is represented by [3]:

$$H(e^{j\omega}) = \sum_{n=0}^{(M-1)} h(n) e^{-j\omega n}, \quad -\pi < \omega \le \pi \tag{3.5}$$

Now linear phase constraint is described by [3]:

$$\angle H(e^{j\omega}) = -\tau_\phi \omega, \quad -\pi < \omega \le \pi \tag{3.6}$$

Here τ_ϕ is a constant phase delay. Now for Type 1 filter, $h(n)$ has to be symmetrical [3]:

$$h(n) = h(M-1-n), \; 0 \le n \le (M-1) \text{ with } \tau_\phi = \frac{M-1}{2} \tag{3.7}$$

where $h(n)$ shows symmetry about τ_ϕ and τ_ϕ is the index of symmetry. The value of M , in Eq. (4.5), can take even or odd integer values in case of Type 1 and Type 2 filters respectively. The frequency response of Type 1 filter is:

$$H(e^{j\omega}) = \left[\sum_{n=0}^{(M-1)/2} a(n) \cos \omega n \right] e^{-j\omega(M-1)/2} \tag{3.8}$$

3.2.4 Objective Function Formulation for Band-Pass FIR Filter

The objective function for band-pass filter is considered as:

$$\phi = \beta * E_p + (1-\beta) * (E_{S1} + E_{S2}), \quad 0 < \beta \le 1 \tag{3.9}$$

where E_P, E_{S1}, and E_{S2} are calculated following Eqs. (3.10)-(3.12).

$$E_P = \frac{1}{\pi} \int_{\omega_{p1}}^{\omega_{p2}} (1 - H(\omega))^2 d\omega = \left(\frac{\omega_{P2} - \omega_{p1}}{\pi} \right) - 2b_1^T P_1 + b_1^T Q_1 b_1 \tag{3.10}$$

$$E_{S1} = \frac{1}{\pi} \int_0^{\omega_{s1}} (H(\omega))^2 d\omega = b_1^T C_1 b_1 \tag{3.11}$$

$$E_{S2} = \frac{1}{\pi} \int_{\omega_{s2}}^{\pi} (H(\omega))^2 d\omega = b_1^T C_1 b_1 \tag{3.12}$$

where E_p represents pass-band error, E_{S1} and E_{S2} are the first and the second stop-band error respectively for band-pass filter.

Here, $H(\omega) = b^T C(\omega)$, $b = [b_1, b_2, ..., b_{N/2}]^T$

P and Q can be defined as :

$$P = \frac{1}{\pi} \int_0^{\omega_p} \cos(A\omega) d\omega \tag{3.13}$$

$$Q = \frac{1}{\pi} \int_0^{\omega_p} \cos(A\omega) \cos(B\omega) d\omega \tag{3.14}$$

In case of pass-band error, the value of C can be measured from the formula as following:

$$C(m,n) = \frac{1}{\pi} \int_{\omega_s}^{\pi} \cos(A\omega) \cos(B\omega) d\omega \tag{3.15}$$

where $A = \frac{N-1}{2} - m$, $m = 0,1,...(M-1)$; $B = \frac{N-1}{2} - n$, $n = 0,1,...(M-1)$, and $H(\omega)$ is the magnitude response of the filter. Thus the goal of our design is to minimize the objective function for band-pass filter as given in Eq. (3.9).

3.3 Simulation Results and Analysis

This section presents the extensive simulation works performed on MATLAB for the design of Type-1FIR band-pass filters using QSCA. Filter responses have been simulated for the filter orders 18 and 28 i.e., the number of coefficients are 19 and 29 respectively. The results have been compared with those of Parks McClellan (PM) and SCA. The convergence speed of QSCA has been compared with that of SCA in this section.

3.3.1 Testing of Benchmark Functions for Convergence Speed Comparison

In the field of optimization using meta-heuristics and evolutionary algorithms, several test cases should be employed to confirm the performance of an algorithm. This is due to the stochastic nature of these algorithms, in which a proper and sufficient set of test functions and case studies should be employed to ensure that the superior results are not obtained by chance. However, there is no clear definition of suitability for a set of benchmark cases studies. Therefore, researchers try to test their algorithms on as many test cases as possible. This work also employs several test functions with different characteristics. These test functions are displayed in tabulated form in this section.

The set of cases studies employed includes two families of test functions: unimodal and multimodal. The benchmark functions used in this paper are listed as follows:

Table 3.1 Unimodal benchmark functions.

Function	Dim	Range
$g_1(x)=\sum_{i=1}^{D} x_i^2$	50	[-100,100]
$g_3(x)=\sum_{i=1}^{D}(\sum_{j-1}^{i} x_j)^2$	50	[-100,100]
$g_4(x)=\max\{\lvert x_i\rvert,1\le i\le n\}$	50	[-100,100]
$g_5(x)=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	50	[-30,30]
$g_6(x)=\sum_{i=1}^{D}(\lfloor x_i+0.5\rfloor)^2$	10	[-100,100]
$g_7(x)=\sum_{i=1}^{D} ix_i^4+random[0,1]$	50	[-1.28,1.28]

Table 3.2 Multimodal benchmark functions.

Function	Dim	Range
$g_8(x)=\sum_{i=1}^{D}-x_i\sin(\sqrt{\lvert x_i\rvert})$	10	[-500,500]
$g_9(x)=\sum_{i=1}^{D}[x_i^2-10\cos(2\pi x_i)+10]$	50	[-5.12,5.12]
$g_{10}(x)=-20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2})-\exp(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)+20+e$	100	[-32,32]
$g_{11}(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}})+1$	50	[-600,600]
$g_{12}(x)=\frac{\pi}{\Pi}\{10\sin(\pi y_1)+\sum_{i=1}^{D-1}(y_i-1)^2[1+10\sin^2(\pi y_{i+1})]+(y_n-1)^2\}+\sum_{i=1}^{D}u(x_i,10,100,4)$ $y_i=1+\frac{x_i+1}{4}$ $u(x_i,a,k,m)=\{\begin{array}{ll} k(x_i-a)^m & x_i>a \\ 0 & -a<x_i<a \\ k(-x_i-a)^m & x_i<-a\end{array}$	10	[-50,50]
$g_{13}(x)=0.1\{\sin^2(3\pi x_1)+\sum_{i=1}^{D}(x_i-1)^2[1+\sin^2(3\pi x_i+1)]+(x_n-1)^2[1+\sin^2(2\pi x_n)]\}+\sum_{i=1}^{D}u(x_i,5100,4)$	10	[-50,50]

The convergence speeds of both SCA and QSCA for all the thirteen benchmark functions mentioned above have been compared by plotting their convergence curves in MATLAB. The convergence curves are illustrated through the following figures:

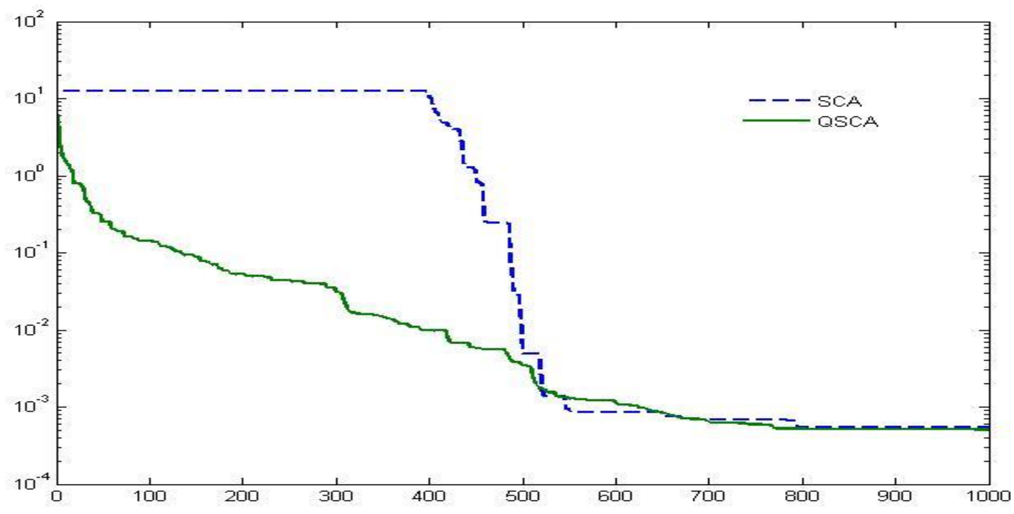

Fig 3.1 Convergence characteristics of SCA and QSCA for the benchmark function $g_1(x)$

The dimension, upper bound and lower bound for this function are 50, 100, and -100 respectively.

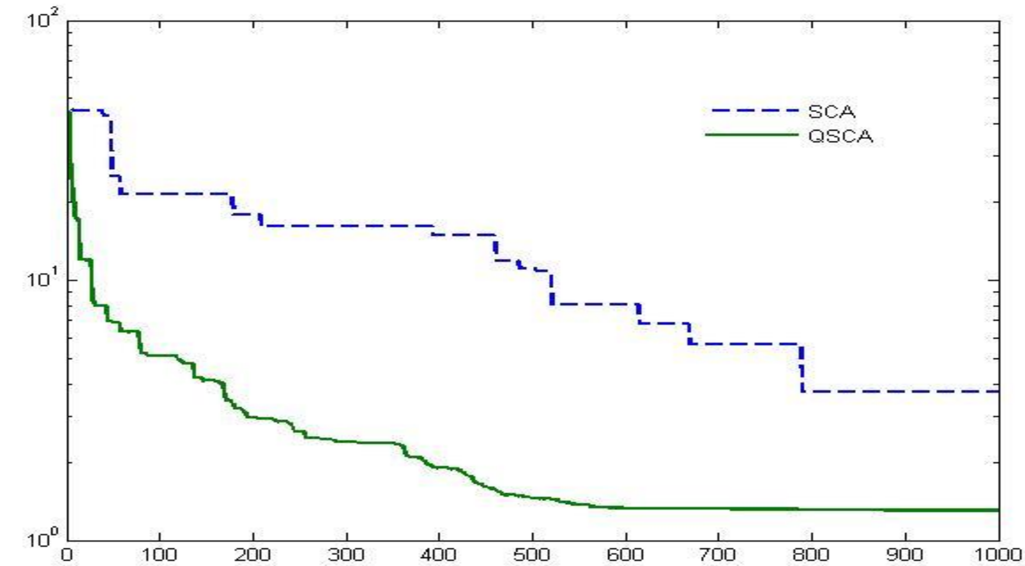

Fig 3.2 Convergence characteristics of SCA and QSCA for the benchmark function $g_3(x)$

The dimension, upper bound and lower bound for this function are 50, 100, and -100 respectively.

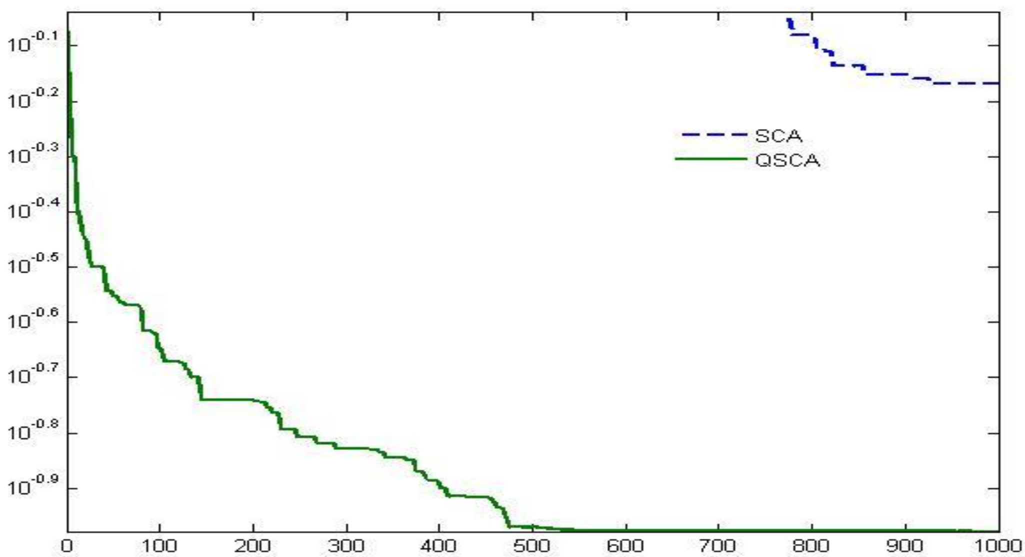

Fig 3.3 Convergence characteristics of SCA and QSCA for the benchmark function $g_4(x)$

The dimension, upper bound and lower bound for this function are 50, 100, and -100 respectively.

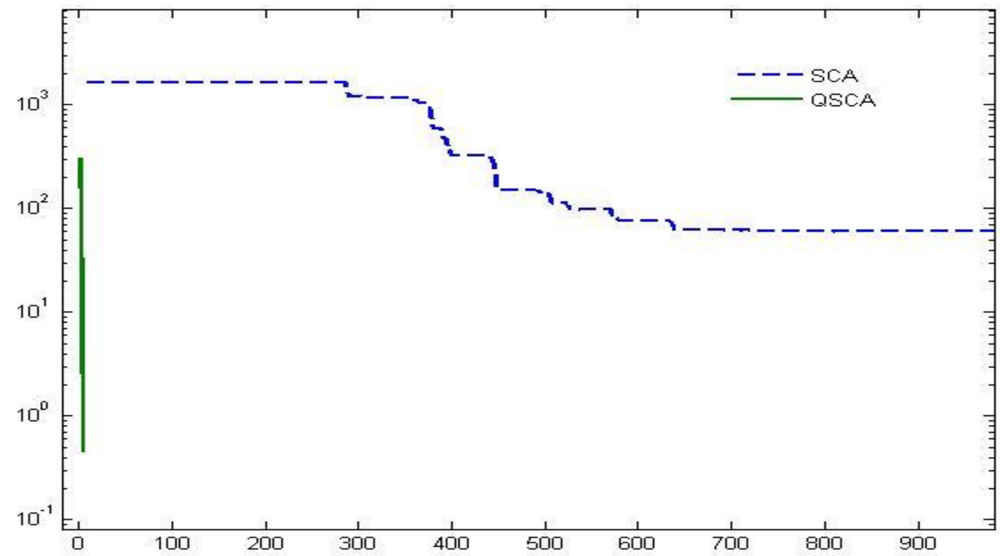

Fig 3.4 Convergence characteristics of SCA and QSCA for the benchmark function $g_5(x)$

The dimension, upper bound and lower bound for this function are 50, 30, and -30 respectively.

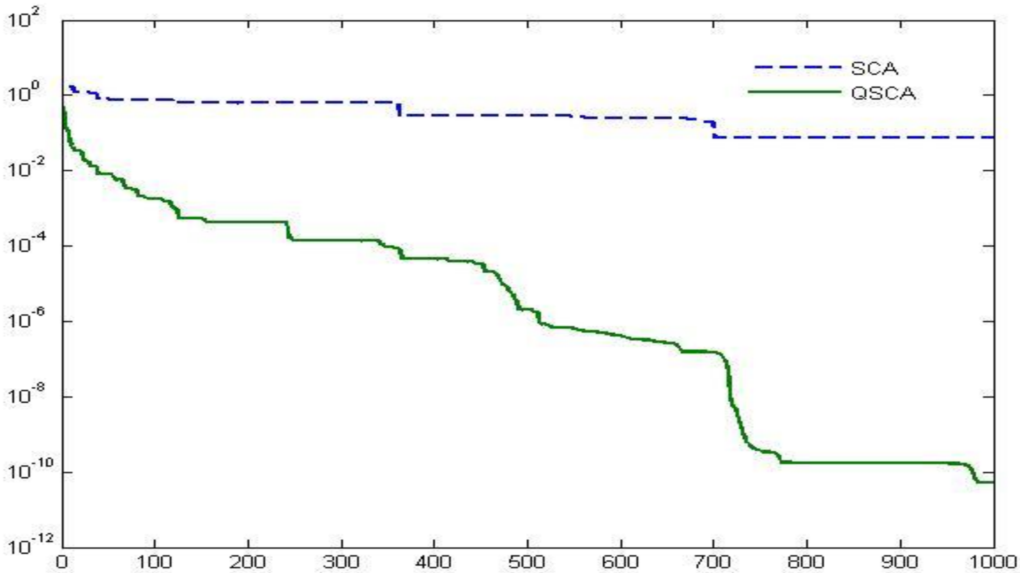

Fig 3.5 Convergence characteristics of SCA and QSCA for the benchmark function $g_6(x)$

The dimension, upper bound and lower bound for this function are 10, 100, and -100 respectively.

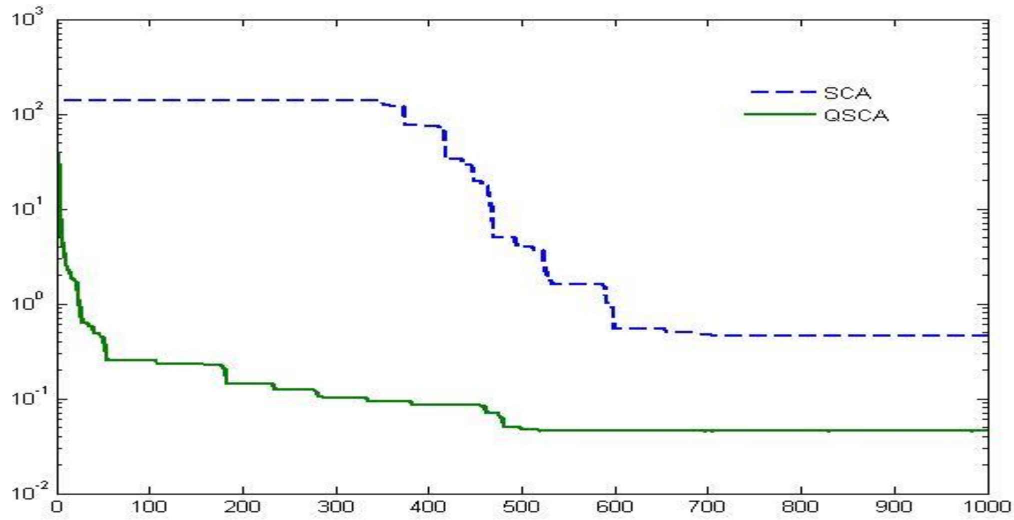

Fig 3.6 Convergence characteristics of SCA and QSCA for the benchmark function $g_7(x)$

The dimension, upper bound and lower bound for this function are 50, 1.28, and -1.28 respectively.

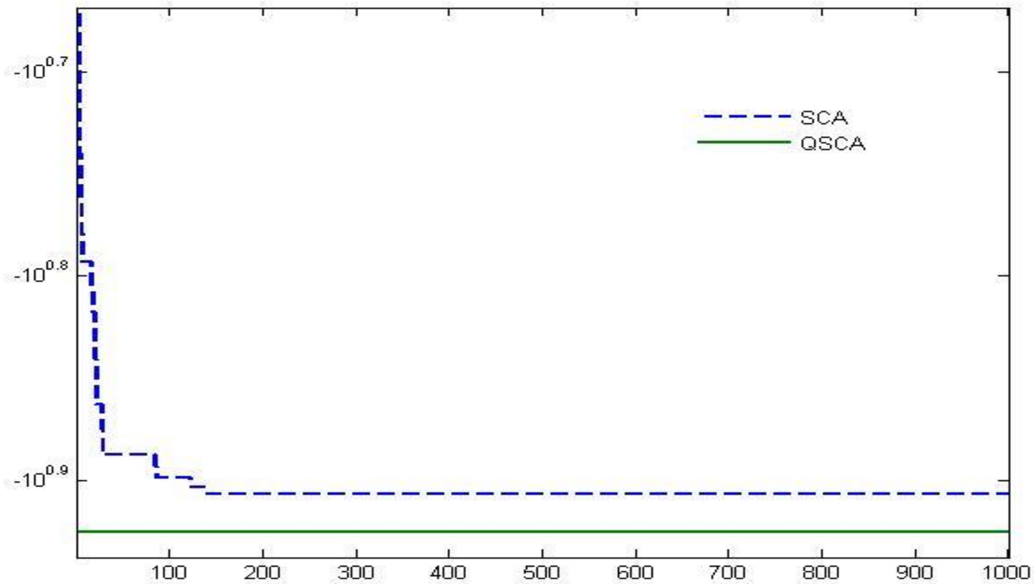

Fig 3.7 Convergence characteristics of SCA and QSCA for the benchmark function $g_8(x)$

The dimension, upper bound and lower bound for this function are 10, 500, and -500 respectively.

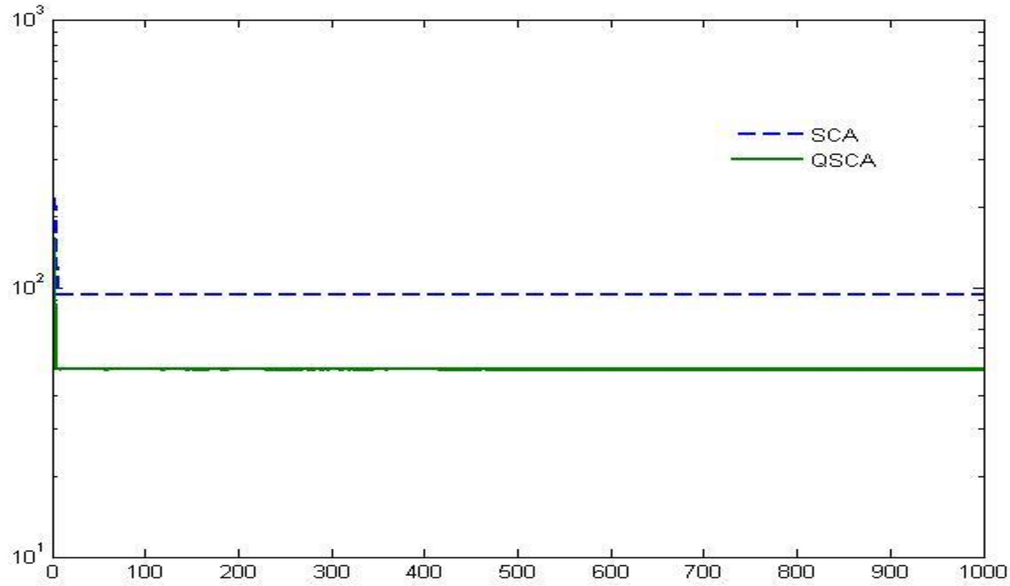

Fig 3.8 Convergence characteristics of SCA and QSCA for the benchmark function $g_9(x)$

The dimension, upper bound and lower bound for this function are 50, 5.12, and -5.12 respectively.

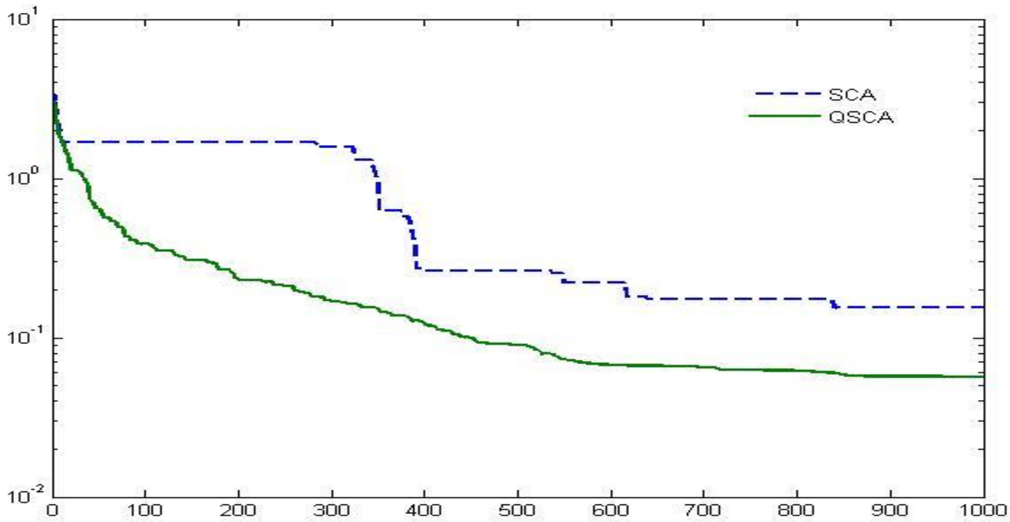

Fig 3.9 Convergence characteristics of SCA and QSCA for the benchmark function $g_{10}(x)$

The dimension, upper bound and lower bound for this function are 100, 32, and -32 respectively.

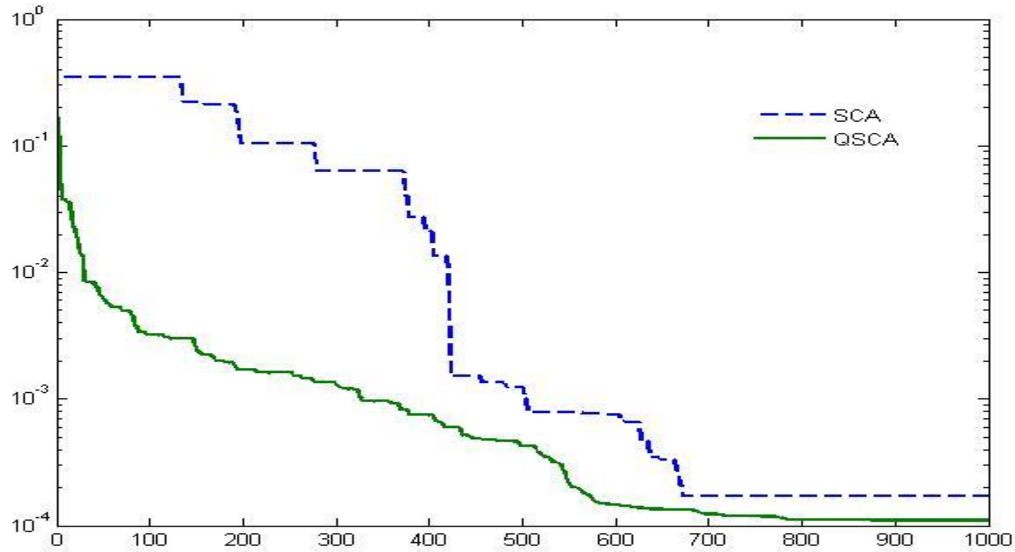

Fig 3.10 Convergence characteristics of SCA and QSCA for the benchmark function $g_{11}(x)$

The dimension, upper bound and lower bound for this function are 50, 600, and -600 respectively.

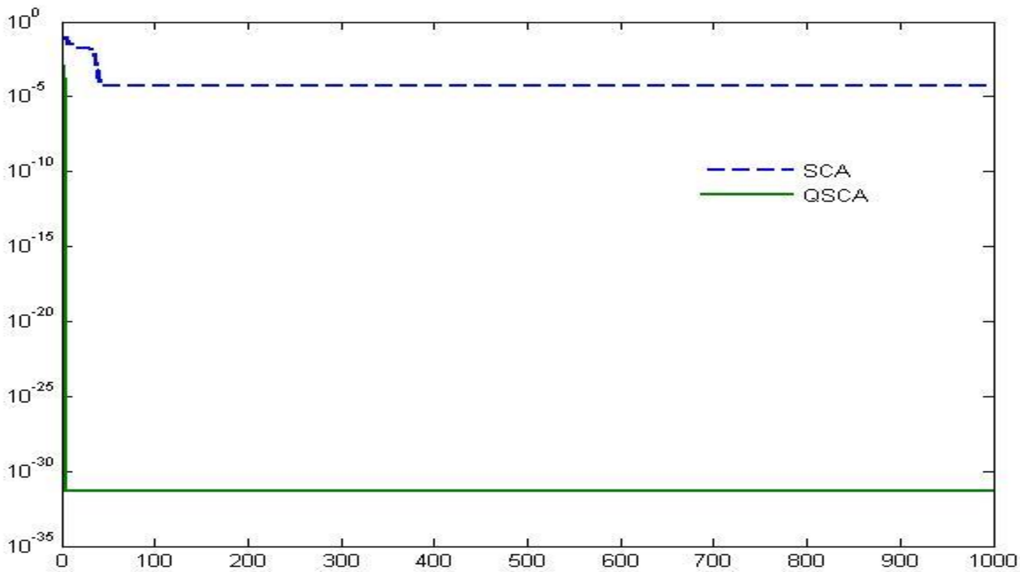

Fig 3.11 Convergence characteristics of SCA and QSCA for the benchmark function $g_{12}(x)$

The dimension, upper bound and lower bound for this function are 50, 50, and -50 respectively.

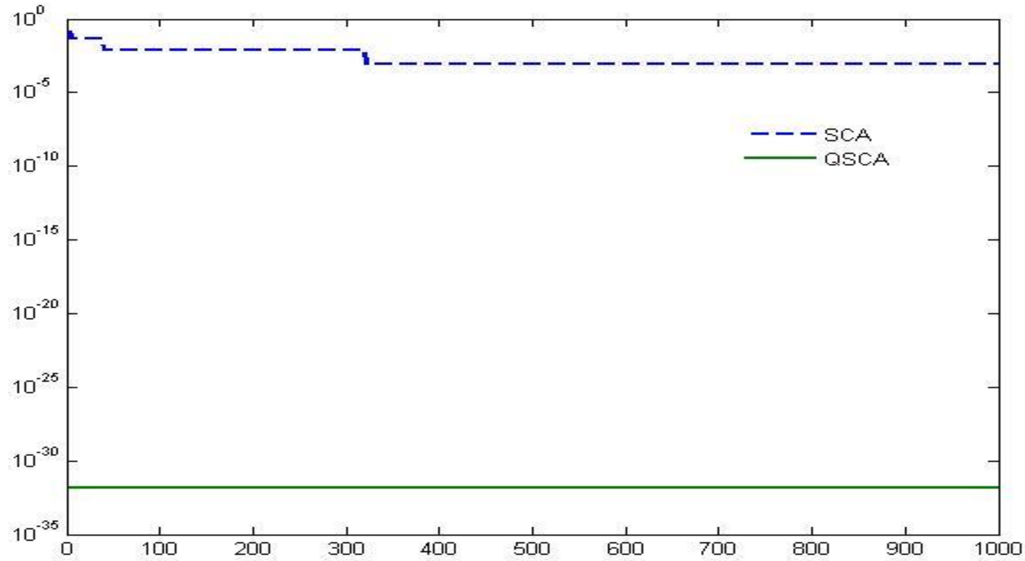

Fig 3.12 Convergence characteristics of SCA and QSCA for the benchmark function $g_{13}(x)$

The dimension, upper bound and lower bound for this function are 50, 50, and -50 respectively.

3.3.2 Comparison of FIR Filter Response for PM, SCA, and QSCA

This section presents the comparison of simulation results of band-pass FIR filter design with the following parameter settings: $\omega_{s1} = 0.2\pi$, $\omega_{p1} = 0.3\pi$, $\omega_{p2} = 0.7\pi$, and $\omega_{s2} = 0.8\pi$, where ω_{s1}, ω_{s2} are stop-band cutoff frequencies and ω_{p1}, ω_{p2} are pass band cutoff frequencies. The results have been obtained utilizing three optimization techniques— PM, SCA, and QSCA. The complete design work is performed using MATLAB 2018B. The type-I band pass filter has been designed as a minimization problem based on Eqs. (3.9-3.15) and the proposed algorithm is applied to minimize the objective function. For order (N) 18, the population size (NP) taken is 20 and the number of functional evaluation (NOFE) is 50,000. For order 28, NP is 20 and NOFE is 1,50,000.

The filter coefficients of Type-1 BPF for the order 18 and 28 obtained through MATLAB simulation by utilizing the above mentioned algorithms are presented below in the Tables 3.3 and 3.4 respectively.

Table 3.3 Optimized coefficients of FIR BP filter of order 18 using PM, SCA, and QSCA

h(n)	PM	SCA	QSCA
h(1) = h(19)	2.29E-16	-0.01953	-0.03295
h(2) = h(18)	1.83E-17	0.003495	-2.28177
h(3) = h(17)	-9.86E-17	0.039441	0.004114
h(4) = h(16)	0.119604	1.60211	6.653995
h(5) = h(15)	-2.85E-17	0.146204	0.009519
h(6) = h(14)	1.83E-17	-0.17252	2.00704
h(7) = h(13)	-5.11E-18	0.000233	0.003304
h(8) = h(12)	-0.31313	-6.10053	-25.153
h(9) = h(11)	2.41E-17	-0.00084	-0.00655
h(10)	0.5	10.00388	38.59253

Table 3.4 Optimized coefficients of FIR BP filter of order 28 using PM, SCA, and QSCA

h(n)	PM	SCA	QSCA
h(1) = h(29)	0.026477	0.741642	1.740664
h(2) = h(28)	5.38E-17	-0.25442	0.003982
h(3) = h(27)	-2.52E-16	0.726394	0.287367
h(4) = h(26)	3.09E-17	0.063385	-0.09743
h(5) = h(25)	-0.04412	-0.84686	-4.39043
h(6) = h(24)	-1.95E-16	0.292684	0.049007
h(7) = h(23)	3.47E-17	-0.77374	-0.35219
h(8) = h(22)	5.77E-17	-0.57806	0.089581
h(9) = h(21)	0.093436	2.6317	10.08663
h(10) = h(20)	-1.07E-16	0.143382	-0.05802
h(11) = h(19)	-8.40E-17	0.642375	0.426137
h(12) = h(18)	3.09E-17	0.785157	-0.13509
h(13) = h(17)	-0.31394	-8.87709	-35.0096
h(14) = h(16)	-6.10E-17	-0.56017	0.10367
h(15)	0.5	12.72726	55.51136

As we know the number of coefficients for filter is always one more than the filter order, hence the total number of coefficients for the order 18 and order 28 are 19 and 29 respectively. Because we are dealing with linear phase filter, the coefficients are also symmetrical around the centre coefficient for both the orders (h(10) for order 18 and h(15) for order 28), as can be the observed from the above tables.

The comparison of performance parameters such as pass-band ripple (R_p) and stop-band attenuation (A_s), obtained in simulating FIR filter design using PM, SCA, and QSCA are demonstrated in the Table 3.5.

Table 3.5 Comparative simulation results of performance parameters for Type-1 BPF

Order (N)	Population size (NP)	NOFE	Method	A_s (in dB)	R_p (in dB)
18	20	50000	PM	19.8713	1.9706
			SCA	26.8451	1.0913
			QSCA	**33.9310**	**1.4429**
28	20	150000	PM	32.7012	0.4132
			SCA	26.8858	1.3939
			QSCA	**39.1590**	**0.2718**

Table 3.5 shows that for order 18, the stop-band attenuation (A_s) and the pass-band ripple (R_p) achieved for the Type-1 band-pass filter using QSCA are 33.9310 and 1.4429 dB respectively. For order 28, the values of A_s and R_p using QSCA are 39.1590 and 0.2718 respectively. This shows that QSCA achieves the best stop-band attenuation and pass-band ripple as compared to those of PM and SCA.

Graphical comparison of BP filters responses using PM, SCA, and QSCA for order 18 and order 28 are illustrated in the figures 3.13 and 3.14 respectively.

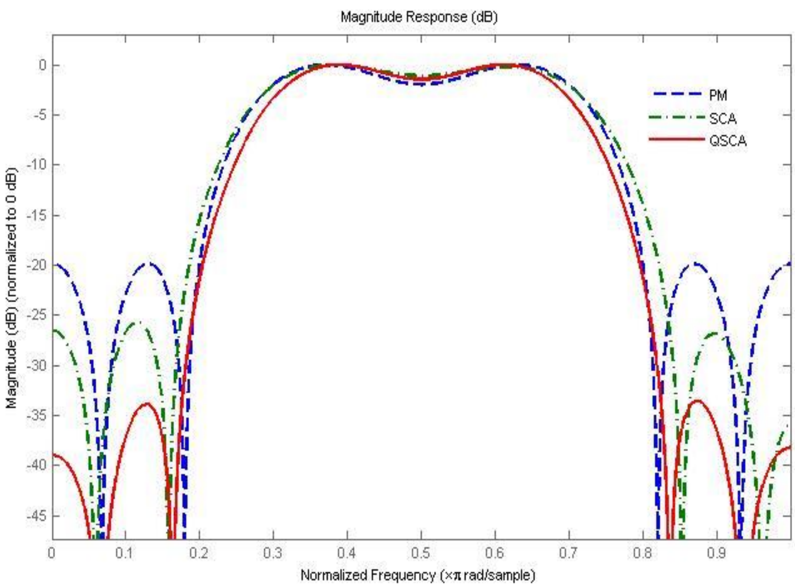

Fig 3.13 Response of BPF for order (N) =18

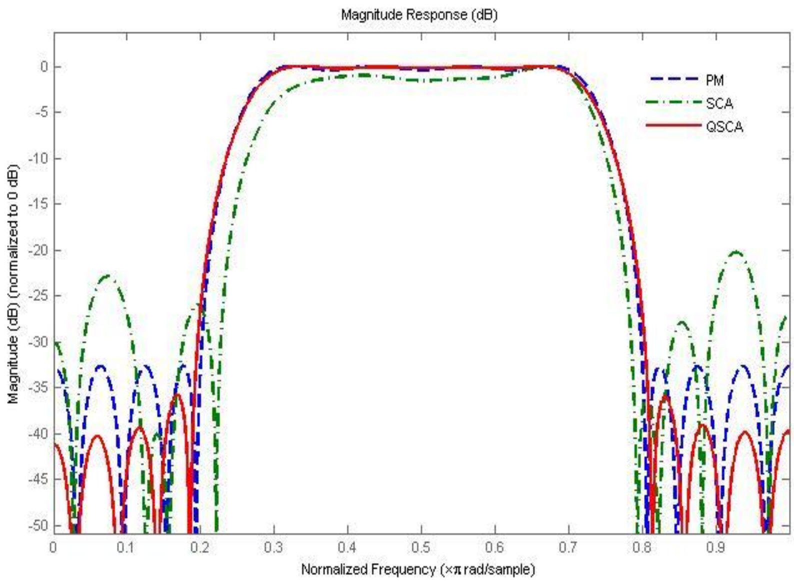

Fig 3.14 Response of BPF for order (N) =28

From the above two figures, it can be observed that the responses obtained for both the orders using QSCA have the lowest pass-band ripple and highest stop-band attenuation compared to the responses obtained using PM and SCA. Hence, it can be concluded that QSCA provides the best magnitude response among the three algorithms.

3.4 Summary

In this chapter, Type-1 band pass filters have been designed using the proposed Quantum inspired Sine Cosine Algorithm (QSCA) and the results have been compared with those of pm and SCA. The simulation results and graphical analysis prove that QSCA is better compared to PM and SCA. Fig (3.1 - 3.12) illustrates the faster converging capability of QSCA compared to SCA for most of the benchmark functions. It not only provides better and faster convergence characteristics but also offers a very good balancing between the performance parameters i.e., the stop-band attenuation (A_s) and the pass-band ripple (R_p) for both higher and lower order BPF as demonstrated in Table 3.5.

Chapter 4

Conclusion and future prospects

In this thesis, a novel optimization technique named as Quantum inspired Sine Cosine Algorithm (QSCA) has been proposed and it is efficiently used for the design of Type-1 FIR band-pass filters. From the simulation results, presented in Chapter 3, it can be easily verified that the proposed algorithm proves itself superior than existing algorithms such as Parks McClellan and the classical Sine Cosine Algorithm. The proposed method provides the best values for stop-band attenuation and pass-band ripple compared to PM and SCA and hence it can be considered as a viable candidate for the design of digital FIR filters.

Although only two optimization methods i.e., SCA and QSCA have been elaborately discussed in this thesis for the design of digital FIR filters but there is still room to improve the performance of the algorithm in the domain of filter design. New and different kinds of meta-heuristic optimization algorithms can also be used for the purposes of complexity reduction in digital filter implementation, minimizing the design error, and increasing the convergence speed. Further, the filters designed by the newly developed algorithm can be implemented on FPGA (Field Programmable Gate Array) platform with less area, reduced power consumption, and low time delay.

The finding of the work has been accepted for publication as per details given below:

A. Sikder, P. Venkateswaran et al., “Design of Band-pass FIR Filter using Improved Sine Cosine Algorithm and its Implementation on FPGA”, IEEE Region 10 Symposium, TENSYMP 2019, IEEE Kolkata Section, Kolkata, June 7 – 9, 2019.

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