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DESIGN OF INFINITE IMPULSE RESPONSE FILTER USING GENETIC ALGORITHM TO MINIMIZE THE RIPPLE IN PASS BAND AND STOP BAND AND TO DECREASE THE TRANSITION WIDTH

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Abstract— *The design of infinite impulse response (IIR) filter has increased attention in the field of signal processing in recent years. This paper presents the design of Band Pass Butterworth and Chebyshev infinite impulse response (IIR) filters with requirement of less ripples in pass band and stop band and small transition width. The Different optimization algorithms are available in literature but the Genetic Algorithm (GA) has been used here for the design of Butterworth and Chebyshev infinite impulse response (IIR) filters due to its simplicity and ease of implementation. The Genetic Algorithm (GA) is a general optimization algorithm, but it needs to be modified to design a digital IIR filter design. These modifications include a method for mapping a filter to an element, evaluation of the fitness function of the IIR filter, creation of an initial population of the IIR filter. The Genetic Algorithm is applied in order to obtain the designed magnitude response (Hn) as close as possible to desired magnitude response (Hd) .The proposed Algorithm has been tested for band pass Butterworth and Chebyshev IIR filter design problems.*

Keywords*-Butterworth Filter, Chebyshev Filter, Infinite Impulse Response (IIR) Filter, Band Pass Filter, Genetic Algorithm, Fitness Function, Generations, Crossover*

I. INTRODUCTION

In signal processing, the function of a filter is to remove unwanted parts of the signal, such as random noise, ripple in pass band and stop band and to extract useful parts of the signal. Filtering is a process by which frequency spectrum of a signal can be modified, re-shaped, or manipulated according to the desired specifications. The digital filter is a digital system that can be used to filter the discrete-time signals [1]. There are two different types of digital filters: finite impulse response (FIR) filters and infinite impulse response (IIR) filters. The FIR filter is that whose impulse response is of finite duration. The output of such a filter is calculated from the current and previous input values. This type of filter is hence said to be non-recursive filter [1]. When a FIR filter is excited by an impulse, it generates a finite number of output values. When the input is removed, the output of the filter eventually decays to zero.

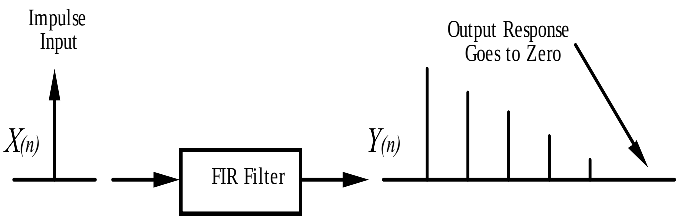

Figure 1. Impulse response of FIR Filter

The IIR filter is one whose impulse response continues for ever in time .The current output of IIR filter depends upon previous output values. This type of filter is hence said to be recursive filter [1].When an IIR filter is excited by an impulse, it produces an infinite number of output values. When the input is removed, the output of the filter may not decay to zero.

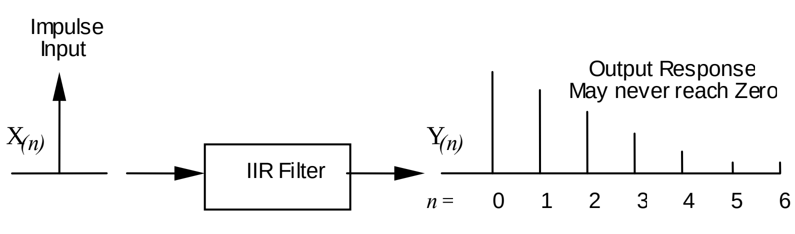

Figure 2. Impulse response of IIR Filter

Infinite impulse response (IIR) filters are widely used in many digital signal processing applications. IIR filters are useful in many fields such as echo cancelations, noise reductions, bio systems, speech recognitions communications and control applications [2][3].The Various design methods are available in literature for designing a practical IIR filter[2]-[5],[7],[8],[10],[11]and [13]. But it is difficult to find the optimum value of filter parameters by using normal numerical methods. Optimization techniques can be used for designing IIR filters. In general optimization can be defined as the process of finding the conditions that give the maximum or minimum value of a function. Similar to many practical problems, in IIR filters, the design variables cannot be chosen arbitrarily; rather, they have to satisfy certain specified functional and other requirements like less ripples in pass band and stop band and small transition width. The Genetic Algorithm (GA) has been used here for the design of Butterworth and Chebyshev infinite impulse response (IIR) filters due to its simplicity and ease of implementation. The Genetic algorithms are widely used to solve constrained minimization problems in many fields of engineering and technology [14]. The Genetic algorithm involves Selection, Reproduction and Mutation. The purpose of selection is to determine the genes to retain or delete for each generation based on their degree of adaptation [5].This paper presents the design of fourth order band pass Butterworth and Chebyshev2 IIR filter using GA.

II. BASICS OF GENETIC ALGORITHM

Genetic algorithms (GAs) are search methods based on principles of natural selection and genetics. GAs encodes the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings which are candidate solutions to the search problem are called chromosomes, the alphabets are called as genes and the values of genes are called alleles. For example, in a problem such as the travelling salesman problem, a chromosome represents a route, and a gene may represent a city [15]. GA is based on a Darwinian "Survival of the Fittest" strategy. Each individual in the population represents a potential solution to the problem at hand [3].Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user specified parameter, is one of the important factors affecting the scalability and performance of genetic algorithms. For example, small population sizes might lead to premature convergence and yield substandard solutions. On the other hand, large population sizes lead to unnecessary expenditure of valuable computational time. Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, we can start to evolve solutions to the search problem using the following steps:

2.1. Initialization

The initial population or generation of candidate solutions is usually generated randomly across the search space.

2.2. Evaluation

Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated.

2.3. Selection

Selection allocates more copies of those solutions with higher fitness values (better chromosome) and thus imposes the survival of the fittest mechanism on the candidate solutions. The main idea of selection is to prefer better solutions to worse ones.

2.4. Recombination

Recombination combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring). The competent performance depends on a properly designed recombination mechanism. The offspring under recombination will not be identical to any particular parent and will instead combine parental traits in a novel manner.

2.5. Mutation

While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutation, but it usually involves one or more changes being made to an individual's trait or traits. In other words, mutation performs a random walk in the vicinity of a candidate solution.

2.6. Replacement

The offspring population created by selection, recombination, and mutation replaces the original parental population.

Repeat steps 2.2–2.6 until a terminating condition is met.

III. IIR FILTER DESIGN USING GENETIC ALGORITHM

The Genetic Algorithm is a general optimization algorithm, but it needs to be modified to design a digital IIR filter design. These modifications include a method for mapping a filter to an element, evaluation of the fitness function of the IIR filter, creation of an initial population of the IIR filter, and the designed filter must be realizable. The final filter design algorithm (FDA) that is developed after the modifications in general GA, by evaluated it for two IIR filter design problems. By defining the transfer function $H(z)$ for a digital IIR filter as [16].

$$H(z)=\frac{N(z)}{D(z)}=\frac{\sum_{i=0}^{\alpha} c_i z^{-i}}{1+\sum_{i=1}^{\alpha} b_i z^{-i}}=K\times\frac{\prod_{i=1}^{\alpha}(z-z_i)}{\prod_{i=1}^{\alpha}(z-p_i)}. \quad (1)$$

Where bi and ci are the coefficients of the polynomial and zi and pi are zeroes and poles respectively. K is the gain factor. α determines the order of the filter. A filter to be realizable the following two conditions must meet [17]

- A causal, linear, time invariant (LTI) system with system function $H(z)$ is bounded input bounded output (BIBO) stable if and only if all the poles of $H(z)$ lie inside the unit circle. $(|p_i|<1)$
- A causal, stable, LTI system with system function $H(z)$ is real if and only if all complex poles and zeros of $H(z)$ have complex conjugate pairs or exist singularly on the real axis.

To design the filter mapped the filter transfer function *Hn*(*z*) to an element *xn*. The coefficients of the polynomial form of *Hn*(*z*) are mapped to the vectors of *xn*. As filter stability requires that all poles *pi* of *Hn*(*z*) must be inside the unit circle. Thus we have put the constraint to the value of *pi*. To meet the minimum phase requirements, same constrain has also been applied to the zeros *zi*, The complex vector is required to map *Hn*(*z*) to *xn*. For this complex vector requirement and *Hn*(*z*) to be real all poles and zeroes must have a complex conjugate pair or they should lie on the real axis. To meet above requirement, we can say, for every complex vector $a_{n,m}$ in *xn*, there must exist another complex vector $a_{n,k}$ where

$$a_{n,k} = a^{*}_{n,m} \quad (2)$$

This relationship between vectors changes the way crossover and mutation can operate. If crossover generates an offspring with a complex vector $a_{n,m}$, the crossover operator must ensure that a complex vector $a_{n,k}$ that satisfies (2) is also generated. The gain K_n *is* not mapped into x_n. This is due to the fact that as the pole and zeros locations are restricted inside the unit circle, the gain factor may lie in the range of $0<K<\infty$. Population management for good performance is a major issue in design problems where GA is used. The random generation of the initial population $P(0)$ of filters and check on $P(g)$ for all g to keep P within the range of search space S is very important. After selecting the value of α, zero and pole locations should be randomly selected for each x_n in $P(0)$.For crossover and mutation process to manipulate vectors without regard to search space S, we have used strategy where any vector representing poles and zeros outside the unit circle is mapped back into the unit circle. Any zero z_i that lies outside the unit circle is mapped to a zero z_i' inside the unit circle with the equation

$$z_i' = \frac{1}{z_i^{*}} \quad (3)$$

As the shape of the filter magnitude response will change when mapping poles from outside to inside the unit circle. Therefore, it is assumed that all poles are located within the unit circle before crossover and mutation are applied. The pole mapping strategy needed to maintain stability can be seen in (3). Equation.3 is equally valid for poles with z_i replaced by p_i. As our main aim is to design and optimize an IIR filter with an arbitrary magnitude response. The fitness function should include both the magnitude responses of the filter undergoing evaluation and the desired magnitude response. The fitness function is evaluated as under:

1. The fitness of x_n is calculated by first mapping the vectors of x_n to the pole and zero pairs of $H_n(z)$.
2. The magnitude response $\left|H_n\left(e^{j\Omega}\right)\right|$ of $H_n(z)$ with a default gain of $K = 1$ is evaluated for all frequency bins Ω.
3. The desired magnitude response $\left|H_d\left(e^{j\Omega}\right)\right|$ is also identified at these same frequency bins.
4. To compensate the gain for $H_n(z)$, $\left|H_n\left(e^{j\Omega}\right)\right|$ is scaled by K_n, where K_n is selected to minimize the error between $K_n\left|H_n\left(e^{j\Omega}\right)\right|$ and $\left|H_d\left(e^{j\Omega}\right)\right|$. This is achieved by forcing the average magnitude value of $K_n\left|H_n\left(e^{j\Omega}\right)\right|$ to equal the average magnitude value of $\left|H_d\left(e^{j\Omega}\right)\right|$. The equation for calculating K_n is

$$K_n = \frac{\sum_{y=1}^{Y} \left| H_d \left(e^{j\Omega_y} \right) \right|}{\sum_{y=1}^{Y} \left| H_n \left(e^{j\Omega_y} \right) \right|} \tag{4}$$

5. The squared error is calculated by squaring the difference between $K_n \left| H_n \left(e^{j\Omega} \right) \right|$ and $\left| H_d \left(e^{j\Omega} \right) \right|$ for all Ω.

6. The squared error values are then weighted by multiplying them with a weighting vector Q that assigns a weighting factor to each frequency bin Ω. This enables certain frequency bins of the magnitude response to contribute more or less to the overall fitness of x_n.

7. Finally, the weighted squared error values are summed and scaled to produce the fitness value of x_n. If $K_n \left| H_n \left(e^{j\Omega} \right) \right|$ is identical to $\left| H_d \left(e^{j\Omega} \right) \right|$, then the fitness value will be zero. The complete fitness function as in [6] is

$$f\left(x_n\right) = \frac{1}{Y} \sum_{y=1}^{Y} \left[K_n \left| H_n \left(e^{j\Omega_y} \right) \right| - \left| H_d \left(e^{j\Omega} \right) \right| \right]^2 Q_y, \tag{5}$$

Where Y is the total number of frequency bins, Ωy is an element of Ω and Qy is an element of Q.

IV. SIMULATION RESULTS

In the present work the fourth-order Butterworth band pass filter is designed with different parameters. The desired magnitude response of fourth-order Butterworth band pass filter has lower and upper 3-dB cutoff points $\Omega_l = \frac{\pi}{4}$ and $\Omega_u = \frac{3\pi}{4}$ and unity pass band gain. The frequency vector Ω for specifying $\left| H_d (e^{j\Omega}) \right|$ and evaluating $K_n \left| H_n (e^{j\Omega}) \right|$ consists of 10,000 frequency bins equally spaced between 0 and π .The weighting vector Q for fitness equation equals 1 for all 10,000 points. Transfer function order α = 4, Population size N = 200, Maximum no. of generation execution (gen_max) = 2000, fit_min = 0, No. of vector per element M = α = 4, probability of crossover (pc) = 0.7 and No of design attempt (attempt_max) = 1 and 5.The magnitude response of the both designed and desired Butterworth band pass IIR filter is shown in figure 3 and figure 6 for attempt_max=1 and attempt_max=5 respectively. The pole-zero plot of Butterworth band pass IIR filter is shown in figure 4 and figure 7 for attempt_max=1 and attempt_max=5 respectively. The pole-zero plotting shows the stability of the system. The pole-zero placements in the desired and designed filters are listed in Table 1. The fitness function convergence is shown in figure 5 and figure 8 for attempt_max=1 and attempt_max=5 respectively. From figure 5, it has been concluded that when the no of design attempt is one, the ending fitness level of the designed filter is approximately 6.6095e-32 and that major fitness improvements ceased after about 1550 generations. Also from figure 8, it has been concluded that when the no of design attempt is five, the ending fitness level of the designed filter is approximately 4.0188e-32 and that major fitness improvements ceased after about 1764 generations. Table 1 gives the results of Butterworth band pass IIR filter. From table 1 it has been concluded that when the no of design attempt is one, the fitness function function has converged with 1550 generation but the gain of the designed filter is obtained less as compared to desired filter gain. The designed filter gain is improved by increase the no of design attempt equal to five and the fitness function (fitness_min) achieves the minimum value equals to 4.0188e-32. The magnitude response of designed Butterworth band pass IIR filter almost matches the desired response with negligible error and less ripples in pass band and stop band. This show the accuracy of proposed algorithm.

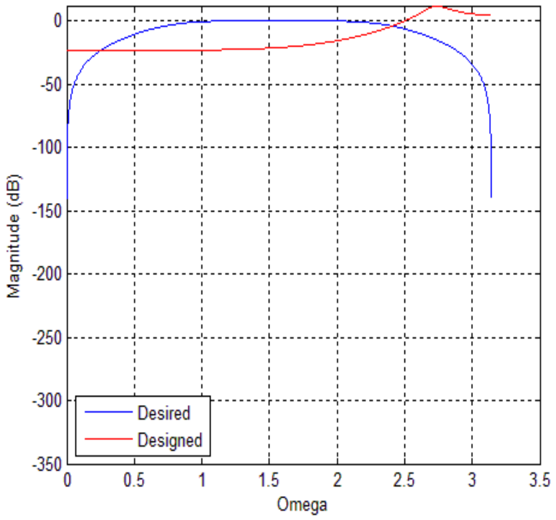

Figure 3. Magnitude response of butterworth band pass filter (attempt_max=1)

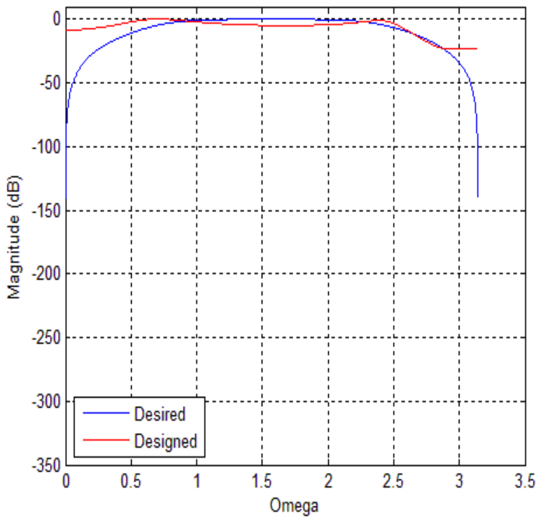

Figure 6. Magnitude response of butterworth band pass filter (attempt_max=5)

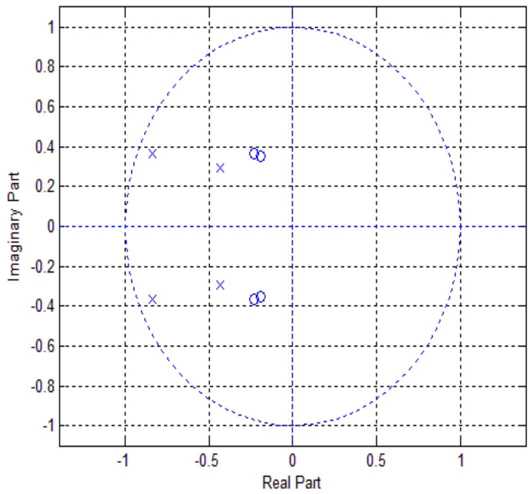

Figure 4. Pole-zero plot of butterworth band pass filter (attempt_max=1)

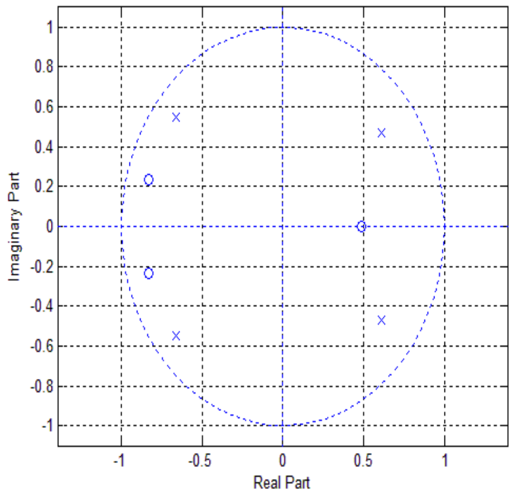

Figure 7. Pole-zero plot of butterworth band pass filter (attempt_max=5)

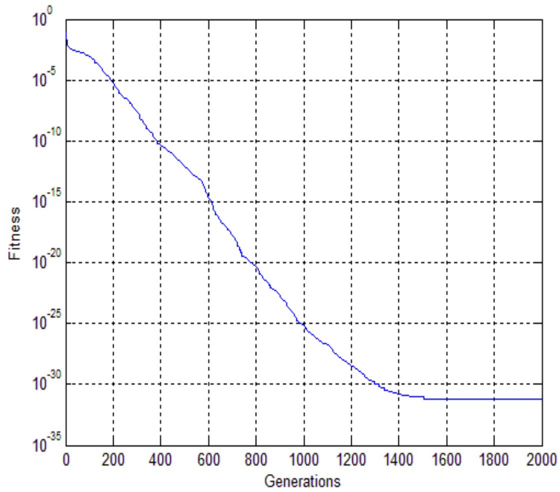

Figure 5. Fitness curve of butterworth

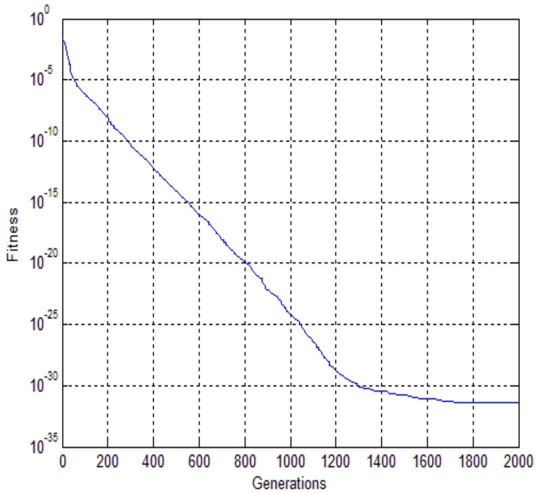

Figure 8. Fitness curve of butterworth

band pass filter (attempt_max=1) ***band pass filter (attempt_max=5)***

Table 1. Results of Butterworth band pass IIR filter

Parameters	Butterworth BPF (attempt_max=1)		Butterworth BPF (attempt_max=5)	
	Desired	Designed	Desired	Designed
Poles	-0.4551+0.4551i	-0.4366+0.2905i	-0.4551+0.4551i	-0.6632+0.5493i
	-0.4551-0.4551i	-0.4366-0.2905i	-0.4551-0.4551i	-0.6632-0.5493i
	0.4551+0.4551i	-0.8368+0.3659i	0.4551+0.4551i	0.6108+0.4715i
	0.4551-0.4551i	-0.8368-0.3659i	0.4551-0.4551i	0.6108-0.4715i
Zeroes	-1+0i	-0.1910+0.3555i	-1+0i	-0.8333+0.2323i
	-1-0i	-0.1910-0.3555i	-1-0i	-0.8333-0.2323i
	1+0i	-0.2295+0.3632i	1+0i	0.4866+0.0020i
	1-0i	-0.2295-0.3632i	1-0i	0.4866-0.0020i
Gain	0.2929	0.1954	0.2929	0.4850
Fitness_min	6.6095e-32		4.0188e-32	
Convergence of fitness function with generation	1550		1764	

The fourth-order Chebyshev2 band pass filter is designed with different parameters. The desired magnitude response of fourth-order Chebyshev2 band pass filter has lower and upper 3-dB cutoff points $\Omega_l = \frac{\pi}{4}$ and $\Omega_u = \frac{3\pi}{4}$ and unity pass band gain. The frequency vector Ω for specifying $|H_d(e^{j\Omega})|$ and evaluating $K_n|H_n(e^{j\Omega})|$ consists of 10,000 frequency bins equally spaced between 0 and π.The weighting vector Q for fitness equation equals 1 for all 10,000 points. Pass band ripple equals to 0.5dB, Transfer function order α = 4, Population size N = 200, Maximum no. of generation execution (gen_max) = 2000, fit_min = 0, No. of vector per element M = α = 4, probability of crossover (pc) = 0.7, No of design attempt (attempt_max) = 1 and 5.The magnitude response of the both designed and desired Chebyshev2 band pass IIR filter is shown in figure 9 and figure 12 for attempt_max=1 and attempt_max=5 respectively. The pole-zero plot of Chebyshev2 band pass IIR filter is shown in figure 10 and figure 13 for attempt_max=1 and attempt_max=5 respectively. The pole-zero plotting shows the stability of the system. The pole-zero placements in the desired and designed filters are listed in Table 2. The fitness function convergence is shown in figure 11 and figure 14 for attempt_max=1 and attempt_max=5 respectively. From figure 11, it has been concluded that when the no of design attempt is one, the ending fitness level of the designed filter is approximately 1.5243e-2 and that major fitness improvements ceased after about 1500 generations. Also from figure 14, it has been concluded that when the no of design attempt is five, the ending fitness level of designed filter is approximately 1.5373e-2 and that major fitness improvements ceased after about 1650 generations. Table 2 gives the results of Chebyshev2 band pass IIR filter. From table 2 it has been concluded that when the no of design attempt is one, the fitness function function has converged with 1500 generation, the gain of the designed filter is almost same response to desired filter gain. The designed filter gain is increase, when no of design attempt equal to five and the fitness function (fitness_min) achieves the minimum value equals to 1.5373e-2. The designed Chebyshev2 band pass IIR filter has almost flat gain in the pass band and has sharp transition slope.

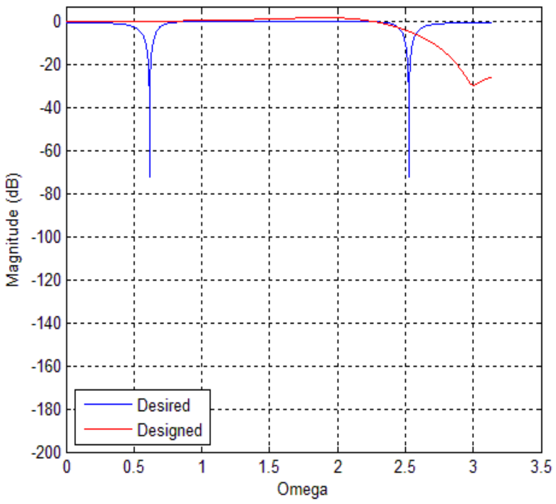

Figure 9. Magnitude response of chebyshev type 2 band pass filter (attempt_max=1)

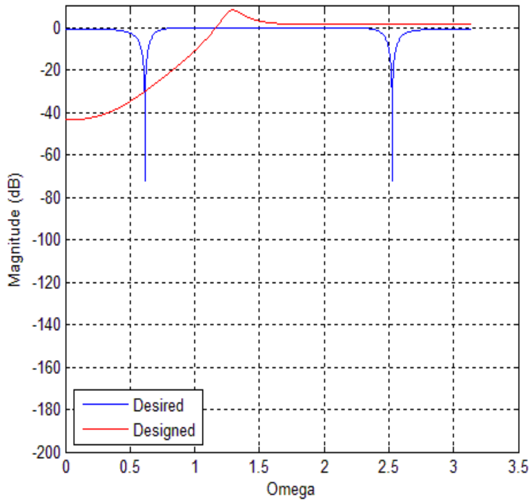

Figure 12. Magnitude response of chebyshev type 2 band pass filter (attempt_max=5)

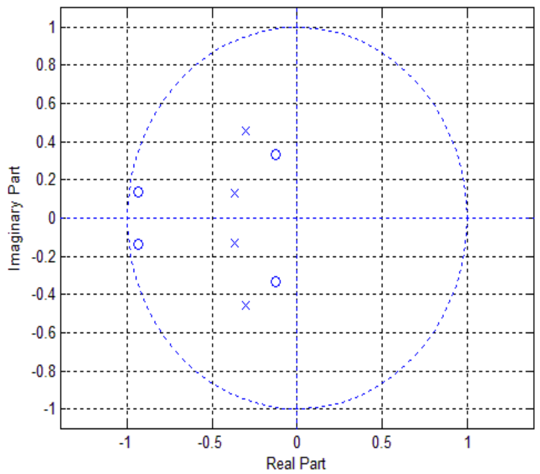

Figure 10. Pole-zero plot of chebyshev type 2 band pass filter (attempt_max=1)

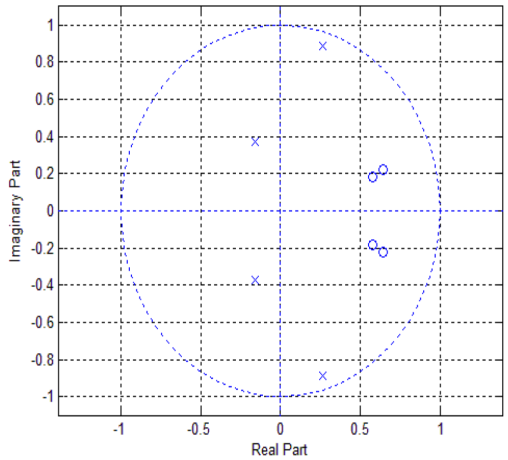

Figure 13. Pole-zero plot of chebyshev type 2 band pass filter (attempt_max=5)

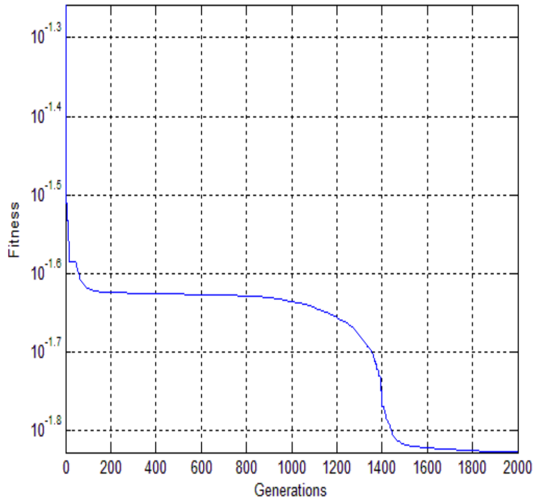

Figure 11. Fitness curve of chebyshev type 2 band pass filter (attempt_max=1)

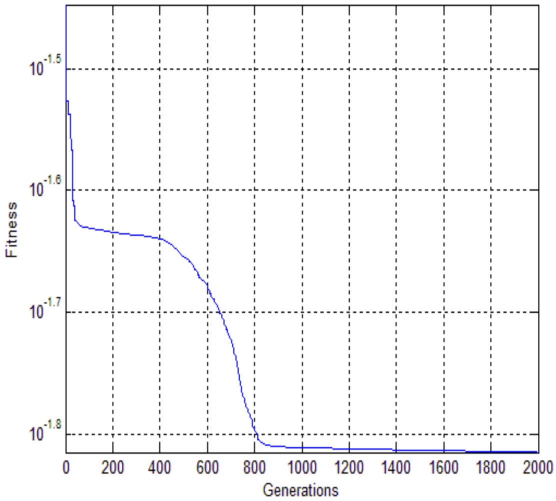

Figure 14. Fitness curve of chebyshev type 2 band pass filter (attempt_max=5)

Table 2. Results of Chebyshev2 band pass IIR filter

Parameters	Chebyshev type 2 BPF(attempt_max=1)		Chebyshev type 2 BPF(attempt_max=5)	
	Desired	Designed	Desired	Designed
Poles	-0.7473+0.5415i	-0.3689+0.1335i	-0.7473+0.5415i	-0.1585+0.3749i
	-0.7473-0.5415i	-0.3689-0.1335i	-0.7473-0.5415i	-0.1585-0.3749i
	0.7473+0.5415i	-0.3006+0.4601i	0.7473+0.5415i	0.2660+0.8896i
	0.7473-0.5415i	-0.3006-0.4601i	0.7473-0.5415i	0.2660-0.8896i
Zeroes	-0.8165+ 0.5774i	-0.9330+0.1371i	-0.8165+ 0.5774i	0.6407+0.2227i
	-0.8165-0.5774i	-0.9330-0.1371i	-0.8165-0.5774i	0.6407-0.2227i
	0.8165+0.5774i	-0.1276+0.3306i	0.8165+0.5774i	0.5812+0.1811i
	0.8165-0.5774i	-0.1276-0.3306i	0.8165-0.5774i	0.5812-0.1811i
Gain	0.8460	0.7042	0.8460	1.217
Fitness_min	1.5243e-2		1.5373e-2	
Convergence of fitness function with generation	1500		1650	

V. CONCLUSION

This paper presents the design of Butterworth and chebyshev2 band pass IIR filter. The Genetic algorithm has been modified to design the filter with low ripples in both pass band and stop band. The results show that the magnitude response of the designed Butterworth and Chebyshev2 band pass IIR filter almost matches the desired response. This shows the accuracy of the proposed algorithm. The pole-zero plots shows the stability of the system for both filter methods. The gain of the filter is increases as the number of design attempt increase for both filters. The Chebyshev2 band pass filter has taken less number of generations to achieve minima as compare to Butterworth band pass filter. The designed Butterworth band pass filter has almost flat gain in the pass band and stop band. The designed Chebyshev2 band pass filter has also almost flat gain in the pass band and has sharp transition slope. As in Butterworth filter design, the fitness function has converged with 1764 generations and achieves fitness minimum value of is approximately 4.0188e-32 and in Chebyshev2 filter design, the fitness function has converged with 1650 generations and achieves fitness minimum value of is approximately 1.5373e-2 with number of attempt equals to 5. It has been concluded that the minimum value of fitness function can be achieve by increase the value gen_max and no of attempt to design the both filters. Further research will focus on design of low pass, High pass, Band stop Butterworth and Chebyshev type 1 and type 2 filters by proposed algorithm.

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