DIGITAL FILTER DESIGN USING SOFT COMPUTING APPROACHES:A REVIEW

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***Abstract*— Soft computing refers to a collection of computational techniques which study, model, and analyze very complex phenomena those for which more conventional methods have not yielded low cost, analytic, and complete solutions. In this review paper, we have discussed how various soft computing approaches have improved the results and performance of the designed FIR and IIR filter.**

***Index Terms*— BBO, DE,FIR filter, GA, IIR filter, PSO.**

I. Introduction

The term soft computing was proposed by the inventor of fuzzy logic, Lotfi A. Zadeh. He describes it as "Soft computing is a collection of methodologies that aim to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost."Components of soft computing includes: Neural networks (NN), Support Vector Machines (SVM), Fuzzy logic (FL), Evolutionary computation (EC), including: Differential evolution (DE), Biogeography based optimization (BBO), Genetic algorithms (GA), Ant colony optimization (ACO), Particle swarm optimization (PSO).In this paper we will discuss about Evolutionary Computation. Evolutionary Computation is a general term for several computational techniques inspired by biological evolution like GA, BBO, PSO, DE etc.

Differential Evolution (DE) is a simple yet powerful population-based, direct search algorithm with the generation and-test feature for global optimization problems using real valued parameters. DE uses the distance and direction information from the current population to guide the further search.

Biogeography based optimization (BBO) is a population based evolutionary algorithm (EA) depending on biogeography. Biogeography is the analysis of the geographical distribution of biological organisms. BBO is an evolutionary algorithm that optimizes a function by iteratively and stochastically for refining candidate solutions with respect to a given degree of quality, or fitness function.

BBO fundamentally depends upon following theory[1].

A. Migration: The BBO migration approach in which we split whether to migrate from one region to other or not. The migrate rate of each solution are used to probabilistically part of features between solutions. BBO migration is used to amend existing habitat. The migration rises when LSI occurs. When species are less and well-suited with their habitat then they migrate.

B. Mutation: The resolution of mutation is to upsurge the habitat among the population. In BBO, the mutation is used to upsurge the diversity of the population to acquire good solution.

Genetic algorithms (GA) are inspired by Darwin's theory of natural evolution. GA search the space of individuals for good candidates. The chance of an individual's being selected is proportional to the amount by which its fitness is greater or less than its competitors' fitness. Solutions from one population are taken and are used to form a new population by generating offsprings. New population is formed using old population and offspring based on their fitness value. Promising candidates are kept and allowed to reproduce.

GA involves four vital steps as follows [2]

Step 1: Create a preliminary population of random chromosomes or solutions through some means.

Step 2: Evaluate the chromosomes for fitness by means of the principles executed on the essential solution and generate a best set of chromosomes by choosing a number of chromosomes that will best fulfil the necessities levied on the solution.

Step 3: If the high-ranking chromosome in the best set fulfils fully the necessities levied on the solution, outcome chromosome as the essential solution, and halt. Else, move to Step 4.

Step 4: Relate crossover among pairs of chromosomes in the best set to engender more chromosomes and focus certain chromosomes selected randomly for mutations, and revive from Step 2.

*Particle swarm optimization (PSO)*emulates the swarm behaviour of insects, animals herding, birds flocking, and fish schooling where these swarms search for food in a co-operative manner. Each member in the swarm familiarises its search pattern by acknowledging from its own experience and other members experiences. These singularities are studied and mathematical models are created. Each particle has a fitness value and a velocity to adjust its flying direction according to the best experiences of the swarm to search for the global optimum in space.

Ant Colony optimization (ACO) is a technique which includes noticing the behaviour of ants taking into consideration TSP(Travelling Salesman Problem) which is nothing but the way how a salesman gets to know and selects the shortest path available out of other paths or routes. In a similar manner, in ACO each ant in a group follows the shortest path with the help of a liquid called Pheromes present in ants which help them to do so to reach to their destination and to keep and collect their food [4].

II. FIR Filter Design Approaches

A. *GA/PSO Approach[8]*

1. Introduction:

Classical gradient based approaches are not efficient enough for accurate design and thus evolutionary approach is considered to be a better choice. A hybrid of Genetic Algorithm and Particle Swarm Optimization algorithm with varying neighbourhood topology, namely Genetic Lbest Particle Swarm Optimization with Dynamically Varying Neighbourhood (GLPSO DVN) is used to find the filter coefficients.The hybrid algorithm is found to produce fitter candidate solutions. GLPSO DVN gives accurate solutions, thus minimizing error to higher extent.The flowchart in Fig. 1 is showing how generations are formed in the algorithm.

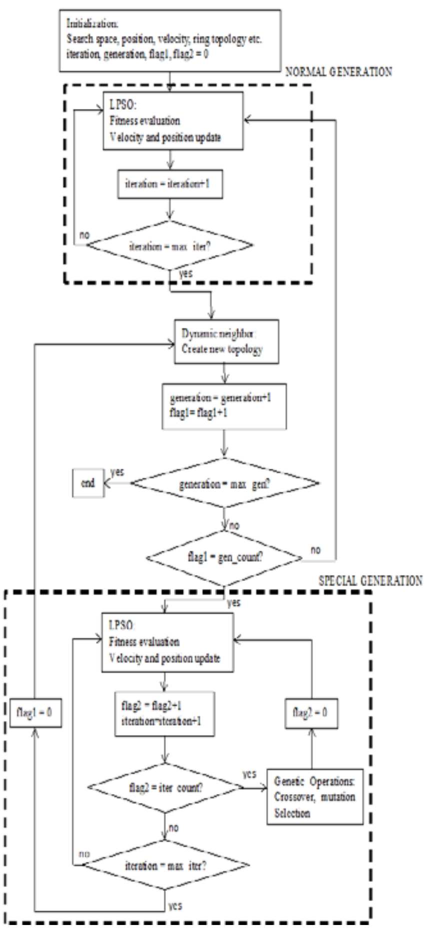

Fig.1 Flowchart showing algorithm of GLPSO[8]

2. Design Parameters:

To design a filter, various filter parameters come into picture. They are passband and stopband cut-off frequencies (w_p and w_s), passband and stopband ripple (δ_p and δ_s), attenuation factor in stopband and transition width. The parameters are totally determined by the filter coefficients [5], [6]. For the designed filter, the passband and the stopband frequencies are 0.3 and 0.4 (normalized with respect to π) and the transition width (w_s-w_p) is 0.1. The passband and stopband ripples are shown [7].

Table 1: Design parameters used in the algorithm[8]

Parameters	Values
Acceleration Coefficient *(c1, c2)*	1.49445
Inertia weight *(w)*	0.729
Maximum Fes	5000
population size	25
max_iter	20
max_gen	3
mutation probability	.05
crossover rate	80%

3. Methodology:

Two types of flag namely flag1 and flag2 have been used that is shown in Fig.1. Flag1 denotes the beginning of new generation i.e. the reconstruction of ring topology is done. Flag1 increases with generation and when it reaches a certain value it reset to zero and Genetic operations are carried over that generation along with PSO. Flag2 denotes in which iterations of that generation genetic operations are done. So, we can identify two types of generation, normal generation and special generation. In normal generation particles go through Lbest PSO. In the end of every generation reconstruction of ring topology is done. In special generation particles go through genetic operations along with Lbest PSO.

4. Results:

The filters are designed to optimize the coefficients which give the best frequency response. This is determined by the ripples on the passband and the stopband. The desired ripple in this problem on the passband δ_p is 0.1 and that on the stopband δ_s is 0.01. In each case, passband and stopband cut off frequencies are 0.25 and 0.3 respectively and the cut-off frequency of the ideal filter is 0.275 (all normalized with respect to π. Filters with 20 coefficients (19th order filters) are designed.

B. *DE/BBO Approach[11]*

1. Introduction:

In this approach,we hybridize DE with BBO and propose a hybrid migration operator to generate the promising candidate solution. And then, the DE/BBO algorithm is proposed based on the hybrid migration operator.Due to the hybrid migration operator, DE/BBO is able to balance the exploration and the exploitation. In addition, the hybrid migration operator can make the good solutions share more information with the poor ones, meanwhile, it can prevent the good solutions from being destroyed during the evolution.

2. Methodology:

Hybrid migration operation is the main operator of DE/BBO, which hybridizes the DE operator with the migration operator of

BBO.By incorporating the hybrid migration operator into DE, the DE/BBO approach is developed and shown in Algorithm 1.

Algorithm 1: The main procedure of DE/BBO
Generate the initial population P
Evaluate the fitness for each individual in P
while The halting criterion is not satisfied do
For each individual, map the fitness to the number of species
Calculate immigration rate λ_i and emigration rate μ_i for each individual X_i
Modify the population with hybrid migration operator shown in algorithm 3.
for i = 1 to NP do
Evaluate the offspring U_i
if U_i is better than P_i then
$P_i=U_i$
end if
end for
end while.

3. Design Parameters:

Thevarious Design parameters used in Filter design are indicated in Table2.

Table 2 Various Design Parameters used[11]

Parameter	Value
Population size: NP	100
Habitat modification probability	1.0
Maximum immigration rate: I	1.0
Maximum emigration rate: E	1.0
Scaling factor: F	rndrealð0:1; 1:0Þ
Crossover probability: CR	0.9
DE mutation scheme	DE/rand/1/bin
Value to reach: VTR	10^{-8}, except for f07 of VTR = 10^{-2}

4. Results:

In order to balance the exploration and the exploitation of DE, a hybrid DE approach, called DE/BBO, which combines the exploration of DE with the exploitation of BBO has been proposed.Since the hybrid migration operator has a good trade-off between the exploration and the exploitation, it makes our proposed DE/BBO approach be very effective and efficient.

III. IIR FILTER DESIGN APPROACHES

A. *GA/BBO Approach[12]*

1. Introduction:

A novel design strategy of Butterworth IIR filter has also been proposed. It considers two most effective hybrid optimization techniques GA and BBO. The results show that GA and BBO based filter designer is able to find transfer function required for given magnitude response. The proposed algorithm doesn't take unnecessary computation time and good in exploiting the solution as the solution doesn't die at the end of each generation. Hence, the performance of proposed hybrid algorithm outcomes the performances of previous proposed algorithms for designing of a digital filter. The simulated results show that the design filter is highly stable and the filter gain is exactly same as that of the ideal filter. The magnitude of the filter is less than one (<1).

2. Methodology:

Filter Design: The transfer function H(z) for a digital filter, given as:

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

Where b_i and$c_i$are coefficients of a polynomial.$p_i$andz_i are poles and zeros of the factored form respectively. K, gain factor is essential for equality between the polynomial and factored form. Order of $H(z)$ is calculated byα.

Properties of $H(z)$ used in design and optimization of designed filter are:

a) Linear Time Invariant (LTI) causal system with system function i.e. $H(z)$ is Bounded Input Bounded Output (BIBO) stable only if all the poles of $H(z)$ lie inside the unit circle i.e.$|p_i| < 1$.
b) Stable and casual LTI system with system function i.e. $H(z)$ is real only if all complex zeros and poles of $H(z)$ have complex conjugate pairs or occur singularly on the real axis.

Fitness Function: Fitness of $x_n$is evaluated by mapping vectors of $x_n$with the zeros and poles of$H_n(z)$. Thereafter, the magnitude response $|H_n(e^{j\omega})|$ of $H_n(z)$with by default gain of $K = 1$ is calculated for all frequency bands ofω. To recompense for unity gain of$H_n(z)$,$|H_n(e^{j\omega})|$is measured byK_n. Here$K_n$is selected for minimization of error of $K_n|H_n(e^{j\omega})|$and $|H_d(e^{j\omega})|$. This is attained by driving the magnitude average value of $K_n|H_n(e^{j\omega})|$equal to the magnitude average value of $|H_d(e^{j\omega})|$. If $K_n|H_n(e^{j\omega})|$is alike to$|H_d(e^{j\omega})|$, then only the fitness value will approx. to zero and minimization of error of$K_n|H_n(e^{j\omega})|$and $|H_d(e^{j\omega})|$will take place.The whole *fitness function* is represented by,

$$f(x_n) = \frac{1}{Y}\sum_{y=1}^{Y}\left[K_n|H_n(e^{j\omega y})| - |H_d(e^{j\omega})|\right]^2 Q_y \text{.........(2)}$$

Here Y is the total no. of frequency bands, ω_y is a component ofω, and $Q_y$is a component of$Q$. ω is normally stated in the range of 0 toπ.

3. Design Parameters:

The filter designer program parameters are configured according to the Butterworth transfer function output. Table 3 shows different design parameters used.

Table 3. Various Design Parameters[12]

Parameter	Value	Comment
GA_Alpha	4	Same order as$H_d(e^{j\omega})$.
GA_Crossover Probability	0.7	Probability of crossover.
BBO_Mutation Probability	0.01	Probability of mutation.

BBO_Keep	2	Elitism Parameter: Number of best habitats to keep from one generation to the next.
GABBO_Max Generations	1500	Maximum number of generations per problem.
GABBO_Population Size	200	Number of elements in population.
GABBO_Variable Per Population Member	GA_Alpha	Number of variables per population member.
FF_Wts	All 1's	Fitness Function Weights.
FF_MinFitvel	0	Minimum fitness level

4. Results:

The designed Butterworth IIR filter is stable as the poles and zeroes of the filters are located inside the unit circle.The gain of the designed Butterworth IIR filter is exactly same as that of the ideal filter. The following Table 4 compares the designed filter with the ideal Butterworth filter.

Table 4. Designed filter Vs Ideal filter[12]

Parameter	Ideal Value	Design Value
Gain	0.29289	0.2929
Zeros	1 -1 1 -1	$-0.4487 + 0.6243i$ $0.0680 + 0.3546i$ $-0.4487 - 0.6243i$ $0.0680 - 0.3546i$
Poles	$0.45509 + j0.45509$ $-0.45509 + j0.45509$ $0.45509 - j0.45509$ $-0.45509 - j0.45509$	$0.5194 + 0.0459i$ $0.0786 + 0.5060i$ $0.5194 - 0.0459i$ $0.0786 - 0.5060i$

The specifications of the designed butterworth filter have been shown in Table 5.

Table 5. Specifications of Designed Filter[12]

Parameter	Designed Value
Iterations	1200
Order	4
ω_L and ω_H	¼ and ¾
Magnitude Response $\lvert H(e^{j\omega})\rvert$	Less than 1 $\lvert H(e^{j\omega})\rvert \leq 0.01$ $0.9 \leq \lvert H(e^{j\omega})\rvert 1$

The magnitude response of the designed fourth order Butterworth IIR filter is in the range of 0.01 to 0.9 with lower and upper 3-dB cut off points of $\omega_l = \frac{1}{4}$, and $\omega_u = \frac{3}{4}$.

B. Cooperative Coevolutionary Genetic Algorithm (CCGA)[9]

1. Introduction:

This novel algorithm is a kind of cooperative co-evolutionary genetic algorithm. CCGA has the following characteristics [10]:

1) A complete solution is divided into more than one sub-components, which are represented by several species, respectively.

2) When an individual is evaluated, it should be combined with individuals in other species to form a complete solution.

3) Each species should evolve separately, using a standard GA.

2. Methodology:

To represent the transfer function of a digital IIR filter,the chromosome contains two types of genes, namely: 1) the control gene and 2) the coefficient gene.

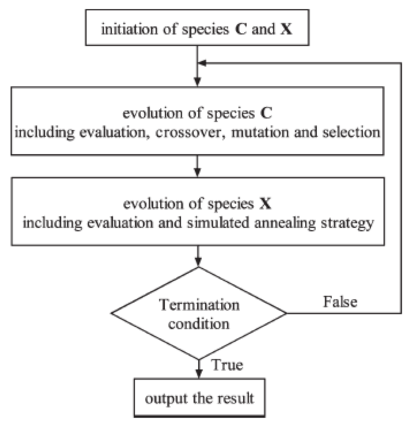

Fig.2 Flowchart of the process of CCGA for digital IIR filter design[9]

The control gene describes the structure of the filter, and the coefficient gene defines the value of the coefficients in each block. In the CCGA, the control genes are separated from the coefficient genes. There are two species in the population, namely 1) the control species C and 2) the coefficient species X. The coding for C is in binary form and in real-number form for X. When an individual in the species C is evaluated, some individuals from the species X need to be selected randomly and combined with the individual from C to get the complete solutions. The values of the solutions determine the fitness of the individual from C. Using the same strategy, species X can be evaluated.

3. Design parameters:

The four types of the filters namely: 1) low-pass (LP); 2) high-pass (HP); 3) band-pass (BP); and 4) band-stop (BS), are designed. The parameters for the design criteria are listed in Table 6and the parameters for genetic operations are given in Table 7.

Table 6. Design criteria[9]

Filter type	ω_p	ω_s	δ_1	δ_2	***Phase Response***
LP	0.2π	0.3π	0.1088	0.17783	Linear in the pass band and the transition band
HP	0.8π	0.7π	0.1088	0.17783	
BP	$[0.4\pi,0.6\pi]$	$[0.25\pi,0.75\pi]$	0.1088	0.17783	
BS	$[0.25\pi,0.75\pi]$	$[0.4\pi,0.6\pi]$	0.1088	0.17783	

Table 7 : Parameters for genetic operations[10]

CONTROL SPECIES	Population size	20
	K_1 for evaluation	10
	Representation	Bit representation
	Crossover	Two-point crossover
	Crossover rate	0.8
	Mutation	Bit-flip mutation
	Mutation rate	0.3
	Evolution control	NSGA-II
COEFFICIENT SPECIES	Population size	40
	K_2 for evaluation	8
	Representation	Real-number representation
	Crossover	Two-point linear crossover
	Crossover rate	0.8
	Mutation	Random disturbance
	Mutation rate	0.5
	Evolution control	SA

4. Results:

CCGA considers the magnitude response and the phase response simultaneously and also tries to find the lowest filter order. The structure and the coefficients of the digital IIR filter are coded separately, and they evolve coordinately as two different species, i.e., the control species and the coefficient species. Table 8 is showing various specifications of the designed filter

Table 8: Specifications of Designed Filter[9]

Filter Type	Magnitude Response		Phase Response Error*	Lowest order	Iteration
LP	$0.9034 \le \lvert H(e^{j\omega})\rvert \le 1,$	$0 \le \omega \le 0.2\pi$	1.4749×10^{-4}	3	274
	$\lvert H(e^{j\omega})\rvert \le 0.1669,$	$0.3\pi \le \omega \le \pi$			
HP	$\lvert H(e^{j\omega})\rvert \le 0.1749,$	$0 \le \omega \le 0.7\pi$	9.7746×10^{-5}	3	657
	$0.9044 \le \lvert H(e^{j\omega})\rvert \le 1,$	$0.8\pi \le \omega \le \pi$			
BP	$\lvert H(e^{j\omega})\rvert \le 0.1654$	$0 \le \omega \le 0.25\pi$ $0.75\pi \le \omega \le \pi$	8.1751×10^{-5}	4	1498
	$0.8920 \le \lvert H(e^{j\omega})\rvert \le 1$	$0.4\pi \le \omega \le 0.6\pi$			
BS	$0.8966 \le \lvert H(e^{j\omega})\rvert \le 1$	$0 \le \omega \le 0.25\pi$ $0.75\pi \le \omega \le \pi$	1.6198×10^{-4}	4	1491
	$\lvert H(e^{j\omega})\rvert \le 0.1733$	$0.4\pi \le \omega \le 0.6\pi$			

* The frequency sampling points in the pass band and the transition band used for calculating the phase response error are 100, 100, 100 and 200 separately.

The non-dominated sorting genetic algorithm is used for the control species to guide the algorithms toward three objectives simultaneously. These two strategies make the cooperative co-evolutionary process work effectively. Comparisons with another genetic algorithm-based digital IIR filter design method by numerical experiments show that the suggested algorithm is effective and robust in digital IIR filter design.

IV. Conclusion

The various types of filters like FIR and IIR have been designed using soft computing approaches.It is found that the soft computing approaches have very well improved the results and performance of the designed filters.

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