Parameter Identification of unknown system using Big Bang-Big Crunch Optimization Algorithm

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Abstract—**A fundamental aspect of signal processing is filtering. Any type of filter can be design by finding the unknown parameters of that filter. This paper presents Big Bang-Big Crunch (BB-BC) Optimization algorithm to solve parameter identification problems in the designing of digital IIR Butterworth filter. Parameter identification methods are classified under the error criterion used in the formulation of the inverse problem. Unlike other heuristic search algorithms, BB-BC Optimization algorithm is relative simple algorithm with relatively few control parameters. Unknown filter parameters are considered as a vector to be optimized by these algorithms. MATLAB programming is used for implementation of proposed algorithms. Experimental results show that the BB-BC Optimization algorithm has faster convergence rate than the other heuristic search space algorithms. BB-BC Optimization algorithm is used for those applications where high convergence speed is required.**

Keywords—**Filter modelling, MATLAB, Butterworth low pass filter, parameter estimation, Error function, Big Bang-Big Crunch Optimization algorithm**

I. Introduction

Digital filter is a system that produces an output digital signal given an input digital signal, in which each sample of the output signal is obtained as a weighted average of a certain number of the previous input and output samples. The two major types of digital filters are finite impulse response digital filters (FIR filters) and infinite impulse response digital filters (IIR).Infinite impulse response filter are those for which the output of the filter at any given time depends upon the present input and past outputs.IIR filters are used when the only important requirements are sharp cut-off filters and high throughput, as IIR filters, especially those using elliptic characteristics, will give fewer coefficients than FIR.The main disadvantage of FIR filter is that considerably more computation power is required compared to an IIR filter with similar sharpness or selectively, i.e. order of an FIR filter, in most case, is considerably higher than the order of an equivalent IIR filter meeting the same specifications, and FIR filter has thus higher computational complexity. The overall amount of hardware component required to implement a FIR filter is also much higher than the one for an implementation of IIR filters. In this paper **IIR** Butterworth filter is taken as a unknown system.

II. Big Bang-Big Crunch Optimization Method

This paper proposes a novel optimization method that relies on one of the theories of the evolution of the universe; namely, the Big Bang and Big Crunch Theory. This theory associated with Big Bang Theory and Big Crunch Theory. The origin of the Big Bang theory can be credited to Edwin Hubble. Hubble made the observation that the universe is continuously expanding due to tremendous explosion. At the point of this event all of the matter and energy of space was contained at one point. What existed prior to this event is completely unknown and is a matter of pure speculation. This occurrence was not a conventional explosion but rather an event filling all of space with all of the particles of the embryonic universe rushing away from each other. The Big Bang actually consisted of an explosion of space within itself unlike an explosion of a bomb were fragments are thrown outward. Edwin Hubble discovered that a galaxy's velocity is proportional to its distance. Galaxies that are twice as far from us move twice as fast. Another consequence is that the universe is expanding in every direction. This observation means that it has taken every galaxy the same amount of time to move from a common starting position to its current position. Just as the Big Bang provided for the foundation of the universe, Hubble observations provided for the foundation of the Big Bang theory.

The Big Crunch is one of the scenarios predicted by scientists in which the Universe's expansion, which is due to the Big Bang, will not continue forever and one day stop expanding and because of gravity it begin to collapse into itself, pulling everything with it until it eventually turns into the biggest black hole ever according to Einstein's Theory of General Relativity Well. Here everything is squeezed when in that hole. Hence this theory is Big Crunch theory. Big Crunch is the consequence of the Big Bang Theory. Systementropy should always increases in big bang theory and always decreases in big crunch theory.

Big Bang - Big Crunch (BB-BC) optimization algorithm relies on both theories: Big Bang and Big Crunch Theory. It was proposed as a novel optimization method in 2006 and is shown to be capable of quick convergence. In this work, local search moves are injected in between the original “banging” and “crunching” phases of the optimization algorithm. These phases preserve their structures; but the representative point (“best” or “fittest” point) attained after crunching phase of the iteration is modified with local directional moves using the previous representative points. This hybridization scheme smoothens the path going to optima and decreases the process time for reaching the global minima. The results over benchmark test functions have proven that BB-BC Algorithm enhanced with local directional moves has provided more accuracy with the same computation time or for the same number of function evaluations. As a real world case study, the newly proposed routine is applied in target motion analysis problem where the basic parameters defining the target motion is estimated through noise corrupted measurement data.

III. IIR DIGITAL FILTER DESIGN

Infinite impulse response filter are those for which the output of the filter at any given time depends upon the present input and past outputs. The output signal from the filter can be non-zero infinitely after the input signal is changed from non-zero to zero.

IIR filters can generally achieve given desired response with less computational time than FIR filters.

$$y[n]=a_0x[n]+a_1x[n-1]+..+a_{M-1}x[n-M]$$
$$-b_1y[n-1]-b_2y[n-2]-...-b_Ny[n-N] \quad (1)$$

The transfer function of IIR filter is given as:

$$H_d(z)=\frac{a_0+a_1z^{-1}+...+a_{M-1}z^{-M}}{1+b_1z^{-1}+b_2z^{-2}+...+b_Nz^{-N}} \quad (2)$$

$$H_d(z)=\frac{\sum_{k=0}^{M}a_kz^{-k}}{\sum_{k=0}^{N}b_kz^{-k}}, \quad \text{where } b_0=1 \quad (3)$$

Based on its frequency response(ω is normalized frequency ranging in [-π to π]), IIR digital filter is expressed as :

$$H(e^{j\omega})=|H(e^{j\omega})|e^{j\Theta(\omega)} \quad (4)$$

$$=\frac{\sum_{k=0}^{M}a_ke^{-jk\omega}}{\sum_{k=0}^{N}b_ke^{-jk\omega}} \quad (5)$$

where

$$|H(e^{j\omega})|^2=\frac{[\sum_{k=0}^{M}a_k\cos(k\omega)]^2+[\sum_{k=0}^{M}a_k\sin(k\omega)]^2}{[\sum_{k=0}^{N}b_k\cos(k\omega)]^2+[\sum_{k=0}^{M}b_k\sin(k\omega)]^2} \quad (6)$$

$$\theta(j\omega)=-\tan^{-1}\frac{\sum_{k=0}^{M}b_k\sin(k\omega)}{\sum_{k=0}^{M}b_k\cos(k\omega)}+\tan^{-1}\frac{\sum_{k=0}^{M}a_k\sin(k\omega)}{\sum_{k=0}^{N}a_k\cos(k\omega)} \quad (7)$$

when a and b are real, the magnitude response $|H(e^{j\omega})|$ is an even function and phase response θ(jω) is an odd function.

A. Filter Modeling:

Block diagram of the system identification process using IIRfilter designed by the different heuristic algorithms is shown in Fig. 1.

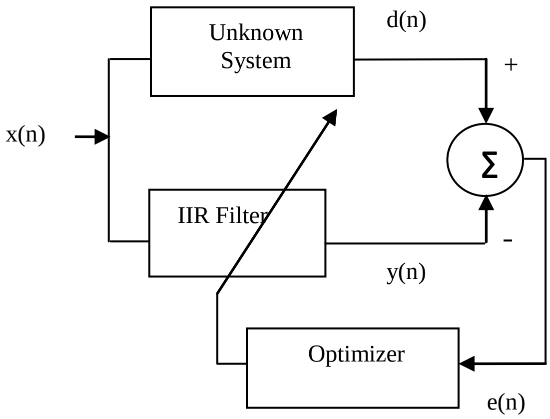

Fig. 1: Schematic of IIR filter for system identification.

For this system, Objective function is typically defined as mean squared error (MSE) between filter output and desired response (response of unknown system) as following:

$$MSE=J(w_H)=\frac{1}{L}\sum_{n=1}^{L}(d(n)-y(n))^2 \quad (8)$$

$$J(w_H)=E[e^2(n)]=E[(d(n)-y(n))^2] \quad (9)$$

Where y(n) is the output of designed filter, d(n) is the output of unknown system, x(n) is the input of the system, e(n) is the filter’s error function, L is the population size for the filter design and w_H is defined as filter coefficient vector expressed as follows:

$$w_H=[b_1,b_2,....,b_M,a_1,a_2,....,a_N]^T \quad (10)$$

The aim is to minimize the MSE (15) by adjusting w_H, so that the frequency response of the designed filter very close approximates the desired response.

B. Problem Formulation

In this paper BB-BC Optimization is used for the designing of IIR filter (IIR filter is widely studied in system identification) in such a way that they can minimize the cost functions (Magnitude error function and group delay error function) of eq. 12.In this case,optimizer estimates the filter coefficients untilerror between the output of the filter and the unknown system is minimized.

1) Problem at hand:

An example has been taken from [my 2nd paper] for simulation study is given as:

$$H_u(z) = \frac{1+1.72z^{-1}+0.62z^{-2}}{1-0.25z^{-1}+0.04z^{-2}} \quad (11)$$

$$H(z) = H_0 \prod_{k=1}^{K} \frac{1+a_1 e^{-j\omega}+b_1 e^{-2j\omega}}{1+c_1 e^{-j\omega}+d_1 e^{-2j\omega}} \quad (12)$$

Eq. (11) and (12) are the transfer functions of unknown plant and IIR filter respectively. Where the optimum values of parameters [a_1, b_1, c_1, d_1] of IIR filter are the [1.72, 0.62, -0.25, 0.04]. In this paper BB-BC Optimization method is used to find the desired coefficients of IIR filter which are[1.72, 0.62, -0.25, and 0.04].

Now $|H(e^{j\omega})| = P(x', \omega)$ is the magnitude of filter,arg $H(e^{j\omega}) = \theta(x', \omega)$ is the phase shift of filter,x'=[a_1, b_1, c_1, d_1 ……….a_k, b_k, c_k, d_k, H_0] represent the parameters of filter.

The Magnitude of IIR filter is defined as:

$$P(x', \omega) = H_0 \prod_{k=1}^{K} \frac{N_k(x',\omega)}{D_k(x',\omega)} \quad (13)$$

Where

$$N_k(x', \omega) = [1 + a_k^2 + b_k^2 + 2b_k(2\cos^2(\omega)-1) + 2a_k(1+b_k)\cos\omega]^{1/2} \quad (14)$$

$$D_k(x', \omega) = [1 + c_k^2 + d_k^2 + 2d_k(2\cos^2(\omega)-1) + 2c_k(1+d_k)\cos\omega]^{1/2} \quad (15)$$

Filter Group delay is defined as:

$$\tau(x', \omega) = -\frac{d\theta(x',\omega)}{d\omega} \quad (16)$$

By solving eq. (13), (14), (15), (16) following equations are obtained:

$$\arg|H(x', \omega)| = \sum_{k=1}^{K}\{\operatorname{atan}\left[-\frac{a_k\sin\omega+b_k\sin(2\omega)}{1+a_k\cos\omega+b_k\cos(2\omega)}\right] - \operatorname{atan}\left[-\frac{c_k\sin\omega+d_k\sin(2\omega)}{1+c_k\cos\omega+d\cos(2\omega)}\right] \quad (17)$$

and

$$\tau(x', \omega) = \sum_{k=1}^{K} -\frac{GN_k}{N_k^2} + \frac{GD_k}{D_k^2} \quad (18)$$

Where $GN_k = (1-b_k)[1 + b_k + a_k\cos\omega]$ (19)

$GD_k = (1-d_k)[1 + d_k + c_k\cos\omega]$ (20)

Now find out the magnitudeP(x',ω) of considered IIR filter, given in eq. (12) by using eq. (13)where the value of zeros and poles of transfer function are the randomly generated particles within search space. Then calculate the desired magnitudeP_1(x',ω) of unknown system, given in eq. (11), byusing eq. (13), where the value of zeros and poles are known [1.72, 0.62, -0.25, and 0.04].

Now determine Group Delay of considered IIR filter and unknown system which are represented as τ(x', ω) and τ_1(x', ω) respectively using eq. (18). The values of [a_k, b_k, c_k, d_k] are [1.72, 0.62, -0.25,0.04].

2) Fitness function (Objective function):

*Magnitude Error function:*This is the mean square error function between amplitude response of IIR filter P(x',ω) and the amplitude response of unknown system P_1(x',ω) with respect to filter coefficients.

$$MSE = J(x', \omega) = \frac{1}{L}\sum_{n=1}^{L}(P_1(x', \omega) - P(x', \omega))^2 \quad (22)$$

Or

$$J(x', \omega) = E[e^2(n)] \quad (23)$$
$$= E\left[\left(P_1(x', \omega) - P(x', \omega)\right)^2\right]$$

Group delay Error function: This is the weighted error function between the deviations of the group delay function (x',ω) from a constant value (τ).

$$GDE(x', \omega) = |\tau(x', \omega) - \tau| \quad (24)$$

These two functions(magnitude error functionsJ(x',ω)andGroup delay Error function) should be as minimum as possible for better designing of IIR filter. The Multi-Objective Optimization problem is solved to find the values of Objective functions $J(x', \omega)$and$GDE(x', \omega)$corresponding to filter parameters that optimize magnitude and group delay.

IV. Big Bang - Big Crunch Optimization Algorithm

The BB-BC Optimization algorithm consists of two phases: a Big Bang phase, and a Big Crunch phase.

In Big Bang phase, candidate solutions are randomly distributed over the search space in a uniform manner Similar to other evolutionary algorithms andshrink these points to a single representative point via a "center of mass" in the Big Crunch phase [14]. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution.

The BB–BC optimization procedure can be briefly outlinedas follows:

1) The initial population of feature vectors is randomlygenerated and spread over the entire search space, allowingalso some individuals (within the range of 10%) begenerated outside the search space. Then all the pointswhich fall outside the prescribed limits are placed atthe boundaries. This will guarantee that the optimumsolution point will not fall outside the domain filled inby the candidate points. The number of individuals inthe population must be big enough in order not to missthe optimum point. However, the population size can besignificantly reduced as the search domain shrinks.

2) The fitness values are computed for every individualand, in the case of maximization, the center of mass 'X_C' is calculated as follows

$$x_j^c = \frac{\sum_{J=1}^{L} \frac{x_j^i}{f^i}}{\sum_{i=1}^{L} \frac{1}{f^i}} \quad \text{i=1,2,3.........L} \qquad (26)$$

Where x_j^c is the *j*th component of center of mass, x_j^i is the *j*th component of *i*th candidate, f^i is fitness of the *i*th candidate, and *L*is the population size in Big Bang phase.

*3)*Determine the boundaries of new contracted space as:

$$\sigma_k = \frac{|x_{\max}^{(k)} - x_{\min}^{(k)}|}{N_{gen} + 1}, \qquad \text{k=1,2,3,4..........n} \qquad (27)$$

Where$N_{gen}$is the generation (iteration) number. Thenthe limits of the parameters are calculated:

$$x_{\min}^{(k)} = \beta x_c^{(k)} + (1-\beta) x_{best}^{(k)} - \sigma_k \qquad (28)$$

$$x_{\max}^{(k)} = \beta x_c^{(k)} + (1-\beta) x_{best}^{(k)} + \sigma_k \qquad (29)$$

Here the empirical parameter β ($0 \le \beta \le 1$) controls theinfluence of the global best solution on the boundariesof new search space.

4) The new search space is now randomly filled with pointsand thus a new population is created.
Hence the algorithm is repeated until the stop criteriaare met. As the search space is contracted with eachnew iteration the algorithm arrives at the optimum pointvery fast.

Steps for obtaining filter coefficients and both Objective functions using BB-BC Optimization method:

*Step 1:*Define search space for both Numerator and Denominator coefficients of IIR filter population size L, order of filter M, stop band frequency and pass band frequency.

*Step 2:*For Butterworth low pass IIR filter design, generate random Numerator coefficient vector X(k) and random Denominator coefficient vector Y(k) within their respective search spaces. Those are the random particle position vectors containing 'L' rows and 'M' columns.

$X_j = [X_{j1}, X_{j2}, X_{j3},............X_{jM}]$(30)

$Y_j = [Y_{j1}, Y_{j2}, Y_{j3},............Y_{jM}]$ (31)

Where j=1, 2, 3,........L.

Step 3: Define the number of iteration1, for finding both best (least) Error functions.
*Step 4:*Calculate Transfer function P(k) and Group delay τ(k) of Butterworth low pass IIR filter for each population size using equ.13 and 18.

Step 5: Calculate desired Magnitude response of unknown filterP_1(k) and desired Group delay response of filter τ_1(k) using equ.13 and 18 where the values of [a_k, b_k, c_k, d_k] are [1.72, 0.62, -0.25,0.04].

*Step 6:*Calculate fitness function for both Magnitude approximation MSE and Group delay approximation GDE by using equ. 22 and 24.

*Step 7:*Define no. of iteration2, for finding best particle X(k), Y(k) and τ(k).

*Step 8:*Find the "center of mass"X_c and Y_c according of each column of X(k) and Y(k) respectively using eq.(26). Best fitness individual can be chosen as the center of mass.

*Step 9:*Determine the boundaries of new contracted search spaces for both numerator and denominator vectors X(k) and Y(k) respectively by using equations (27), (28), (29).
*Step 10:*These new search spaces are now randomly filled with points for both vectors and thus a new population vectors X(k) and Y(k) are created.
Step 11: Now return to the step 7 with increasing the number of iteration2 by 1 until stopping criteria has been met.
Step 12: Now increasing the number of iteration1 by 1. Repeat the procedure from step 3 until stopping criterion has been met.
*Step 13:*Thus, optimal solutions X(k), Y(k), MSE, GDE are obtained. The components of the solution X(k) represent the optimum Numerator coefficients of the filter and the components of Y(k) represent the optimum Denominator coefficients of Butterworth low pass IIR filter.

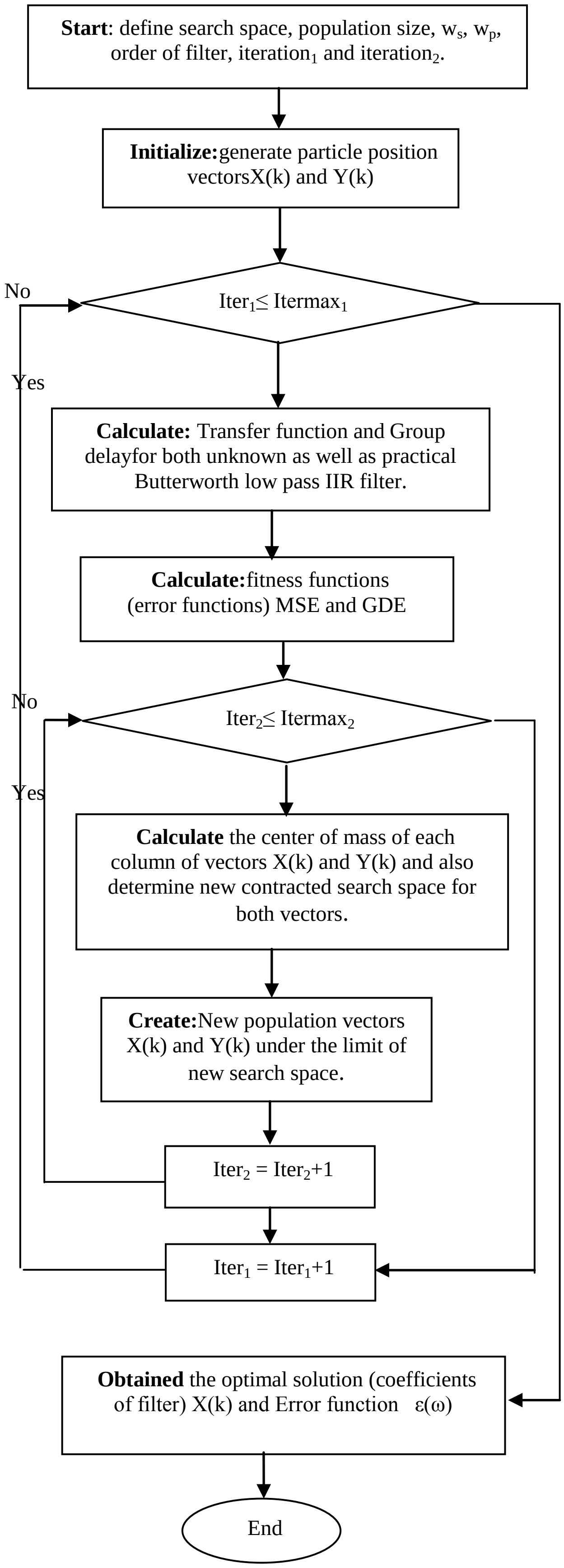

Fig: 2 detail flowchart showing thedesign of digital filters using BB-BC algorithm.

V. RESULT

Butterworth IIR filter is designed using BB-BC Optimization method because IIR filter is mostly used for parameter identification of system. IIR filter design specifications are: The range of randomly generated input vectors are X(n) ϵ [0.5 1.3] and Y(n) ϵ [-0.2 0.02] and filter order is M=2. Length of the input sequence is L=20, population size L=20,$iteration_1$=15 and $iteration_2$=5. In this paper transfer functions of unknown plant and filter are given in Eq. (11) and Eq. (12) respectively, are calculated using BB-BC Optimization method where the parameter vectors [a_1, a_2] and [b_1, b_2]are to be founded their optimum values are[1.72, 0.62]and [-0.25, 0.04] respectively.

Table presents results: filter coefficients, Magnitude error function (MSE) of estimated filter according to Eq. (13) and group delayerror function (GDE)according to Eq. (18) are given over 5 independent runs.

TABLE 2
FILTER COEFFICIENTS, MAGNITUDE AND GROUP DELAY

a	**b**	**c**	**d**	**H(db)**	**τ(db)**
0.97	0.85	-0.21	0.08	0.03	0.10
0.86	0.90	-0.25	0.07	0.05	0.15
0.60	1.12	-0.20	0.03	0.06	0.20
0.58	1.20	-0.23	0.02	0.09	0.20
0.69	1.30	-0.31	0.03	0.12	0.25

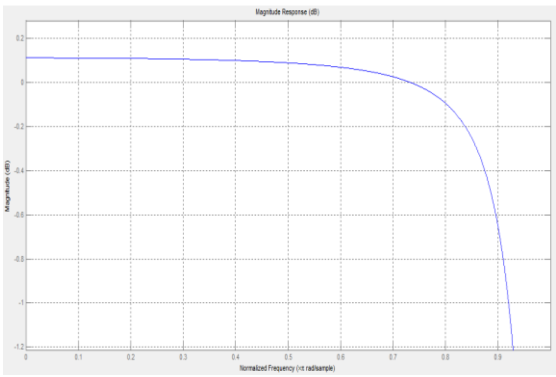

Fig : 3. Optimized “Magnitude (in db)” response of Sec. Order IIR low pass Butterworth filter

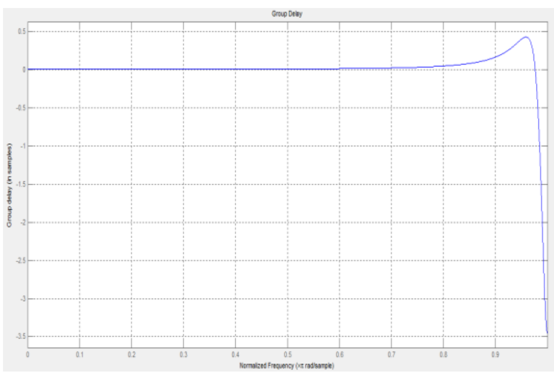

Fig. 4: Optimized “Group delay (in samples)” response of low pass IIR Butterworth filter

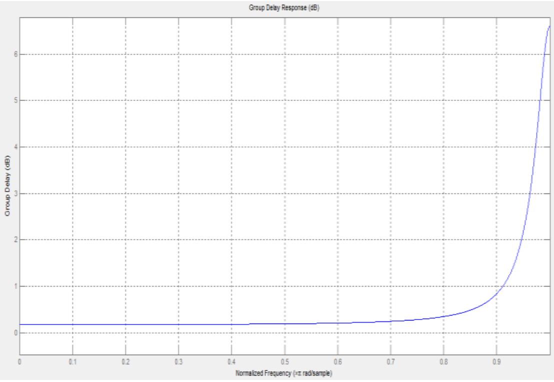

Fig: 5. Optimized “Group delay (in db)” response of Sec. Order low pass IIR Butterworth filter

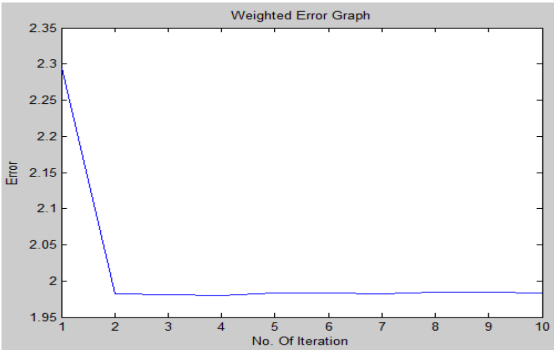

Fig. 6: Magnitude Error graph of Sec. Order IIR Butterworth low pass filter

VI. Conclusion

In this present paper, IIR sec. order Butterworth filter designing is performed based on BB-BC optimization as system identification. The IIR filter is designed so as to approximate prescribed specifications of magnitude with respect to the coefficients of the transfer function.

This is another way to design any system by identifying its parameters using heuristic search methods.In the experimental study, BB-BC algorithm gained better results as compared to PSO on Butterworth IIR filter design case for system identification, with remarkably lower computational cost. BB-BC method has less no. of controlling parameters then the other heuristic approaches like PSO and GA.

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