Finite Wordlength FIR Filter Designing using BBPSO Variants

A Dissertation submitted in fulfillment of the requirements for the degree
of

MASTER OF ENGINEERING
in
Electronic Instrumentation and Control Engineering

Submitted by
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July, 2016

DECLARATION

I hereby certify that the work which is presented in dissertation entitled, "*Finite Wordlength FIR Filter Designing using BBPSO Variants*", in fulfillment of the requirements for the award of the degree of **Master of Engineering** in **Electronics and Instrumentation Control**, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of **Mr. Nirbhowjap Singh**. It refers others researchers work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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CERTIFICATE

Certified that the dissertation entitled, “Finite Wordlength FIR Filter Designing using BBPSO Variants”, which is being submitted by Inderjeet Singh in fulfillment of the requirements for the award of the M.E. in Electronic Instrumentation Control, to Thapar University, Patiala, is a bona-fide record of the candidates own work carried out by him under my supervision and guidance. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other university or institute for award of any degree.

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ACKNOWLEDGEMENT

I would like to take the opportunity to express my gratitude to some people who were involved in this dissertation work. First, I owe my gratitude to my mentor **Mr. Nirbhowjap Singh** (assistant professor), Electrical and Instrumentation department for doing everything from the inception of the work idea to giving incredible suggestions at every step.

I am also thankful to Dr. Ravinder Agarwal, Head of the Department and Mr. Nirbhowjap Singh, PG Coordinator as well as all the faculty members and staff of the Department of Electrical and Instrumentation Engineering for being very supportive to me. I would also like to thank all my batchmates for motivating me all the time whenever I needed them and giving me useful tips. I thank all those who have contributed directly or indirectly to this work.

Lastly, I would also like to thank my parents for their years of unyielding love and encourage. They have always wanted the best for me and I admire their determination and sacrifice.

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NOMENCLATURE

ADE: Adaptive Differential Evolution.
APA: Adaptive Parameter Adjustment.
APSO: Adaptive Particle Swarm Optimization.
BBDE: Bare Bones Differential Evolution.
BBPSO: Bare Bones Particle Swarm Optimization.
CF-AW-PSO: Adaptive Weight Particle Swarm Optimization Algorithm With Constriction Factor.
CRPSO: Craziness Based Particle Swarm Optimization.
CSD: Canonical Sign Digit.
DE: Differential Evolution.
DEWM: Differential Evolution With Wavelet Mutation.
ENSGA: Elitist Nondominated Sorting Genetic Algorithm.
FIPS: Fully Informed Particle Swarm.
FIR: Finite Impulse Response.
FWL: Finite Word Length.
GA: Genetic Algorithm.
IIR: Infinite Impulse Response.
MDE: Modified Differential Evolution.
MOPSO: Modified Particle Swarm Optimization.
NLMS: Normalized Least Mean Square.
NPSO: Novel Particle Swarm Optimization.
ODE: Opposition-Based Differential Evolution Algorithm.
OGA: Orthogonal Genetic Algorithm.
PLS: Projected Least- Square.
PM: Parks-Mcclellan.
POT: Power-Of-Two.
PSO: Particle Swarm Optimization.
PSOCFIWA: Particle Swarm Optimization With Constriction Factor And Inertia Weight Algorithm.
PSOIIW: Particle Swarm Optimization With Improved Inertia Weight,
PSO-LD: Linearly Decreasing Inertia Weight Particle Swarm Optimization.
QP: Quadratic Programming.
QPSO: Quantum-Behaved Particle Swarm Optimization QPSO-M: Modified Quantum-Behaved Particle Swarm Optimization.
RGA: Real Coded Genetic Algorithm.
SA: Simulated Annealing.
SPT: Sum Of Power Of Two.
VFD: Variable Fractional Delay.

ABSTRACT

The utilization of optimization techniques for designing digital filters has become widespread over the recent years. FIR filter optimization is a multi-model problem. The objective of this work is to derive an optimum set of filter coefficients for the given specifications for different type of filters. The optimization problem is phrased as least squared error (LSE) between the specified and designed filter response in the frequency domain. This paper presents an alternative approach for the designing of linear phase Finite impulse response (FIR) high pass filter by using Bare Bone particle swarm optimization (BBPSO) with Cauchy jump strategy technique incorporated with ripple constraint and finite word length constraint in order to achieve flatter frequency response and hardware efficient filter design respectively. The inclusion of finite word length become very crucial when the filter needed to be implement on a digital processor with a fixed point implementation. It is expedient to use BBPSO with jumps for optimization because it require minimum parameter tuning as in the case of other PSO variants. Two case of 20^{th} and 30^{th} order filters have been considered for both low pass and high pass applications. The normalized frequency response justify that proposed BBPSO based technique vanquish the other PSO variants in term of accuracy, robustness, convergence speed and stability. This work also include a case study based on ECG signal filtering for illustration of effectiveness of the designed filter.

CHAPTER 1

INTRODUCTION

A filter is either a hard-wired analog system or a software routine executed on any digital signal processor which can modify, reshape or manipulate the frequency spectrum of any signal as per the design specifications. The basic operations performed by a filter involve amplification, attenuation, rejection and isolation of various frequency components of the signal. Mathematically, a digital filter is basically perform convolution operation of a signal having discrete amplitude and discrete time [1]. Digital filters are advantageous over their Analog counterpart due to their accuracy, modest size, high reliableness and non-critical element tolerance. Design flexibility is an another important advantage of digital filter which provide easy control of frequency response by the mean of coefficient alteration.[2].

Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) are the two broad categories in the digital filter realm. The major advantage of FIR filters that they are : straightforward design and guarantee bounded input-bounded output (BIBO)stability with a linear phase. They are widely accepted because of their flexibility in implementation, precision in performance, adaptability, inherent linearity in phase and reproducibility [3].

The application area of digital FIR filters is very vast. Digital FIR filters can be used for both real-time and off-line (recorded signal) applications. Audio and video signal processing, communication, biomedical instrumentation are few of them. Processing of biomedical signals such as EEG, ECG, EMG and MRI also require digital filtration [4]

1.1 Motivation For Hardware Efficient Filters

Major limitation of FIR filter is that the larger amount of arithmetical calculations concerned throughout the realization that confines its speed and demands a lot of power. This has motivated researchers to touch the sector of hardware economical low-power filter design and consequently this field has been enriched with variety of valuable contributions from several scientists and researchers . FIR filters ar typically characterized by their impulse response coefficients indicating the multiplication with the input signals. Since the multipliers are power and space consuming devices. Therefore, it become essential to keep these multipliers simple as possible for a hardware crucial design. For the sake of simplicity of coefficient fixed point implementation is always preferred. The fixed point implementation replaces the infinite precision coefficients by a fixed wordlength ones [5]. The simplest way for implementing a fixed point scheme is to quantize the coefficients by using fixed number of bits. The use of quantized coefficients results in quantization error which degrades the frequency response. This phenomena is also known as finite word length effect. The association of this effect with other filter specifications makes the filter designing process a real fuzz. Various methods based on both linear programming and non-linear metaheuristic techniques have been used for designing FIR filters. Some of the important optimization techniques have been discussed in the following section.

1.2 Conventional filter design techniques

Window techniques, frequency sampling, equiripple design techniques and weighted least square error are some of the conventional approaches. Frequency sampling approach involves sampling the frequency response at equispaced points by using discrete Fourier transform (DFT) and then computing the filter coefficients by the mean of inverse discrete Fourier transform (IDFT). In window techniques the infinite impulse response of ideal filter is delayed and truncated. Various types of windows such Rectangular, Hamming and Hanning are used in to reduce oscillatory behavior (Gibbs phenomena). Frequency sampling approach provides better control over the critical frequencies as compared to window approach [6].

1.3 Limitations of conventional techniques

The conventional gradient based methods lack in ability to handle multi-objectives and constraints in a single problem [7]. These techniques also seem so be very complex and sluggish on the computational grounds. They become highly inefficient when the search space is complex and have larger dimensions due to the fact that a huge gradient calculation is required. Also these techniques are highly influenced by the the initialization. They seek solution in the neighborhood of initialization points without exploring the more promising areas of search space and ultimately converges to suboptimal solutions. Instability is an another issue related to gradient based techniques. Thse techniques become unstable when the objective function contain multiple sharp peaks. This fact has attracted researchers towards the use various non-linear meta-heuristic optimization techniques for designing optimum filters. The computational limitations of these techniques such as complex derivative, dependence on initialization and requirement of larger memory space have impelled researchers towards the use of meta-heuristic techniques [8].

1.4 Meta-Heuristic Techniques for Filter designing

The meta-heuristic optimization aggregate randomness with some rules to mimic the social behavior of animals. These techniques such as artificial bee colony (ABC), Differential evolution(DE) Genetic algorithm (GA) and Particle swarm optimization (PSO) have been used in the literature by researchers to handle multi-objective, multi-dimensional and constrained optimization problems. These techniques are based on phenomena of natural selection, evolution and swarm intelligence [9–13].For designing FIR filter different optimization techniques have been reported in the literature such as DE[14], GA[15], ABC[16] and PSO. PSO[17] was developed by Kennedy and Eberhart and it simulates the social behavior of fish schooling, bird flocking and swarm of bees. Its ability to handle multi-model problems with minimum number of control parameters, computational efficiency and ease in implementation in context of both coding and parameter tuning makes it prestigious choice towards the designing of FIR filters[18]. Because of this reason it is one of the most explored algorithm used for FIR filter designing. Despite of these advantages PSO also has some unresolved issues like premature convergence due to homogeneity of particles , larger computational time as compared to other mathematical approaches, dependency on particle initialization and parameter initialization, inefficiency of mathematical background and stagnancy of particles in the swarm. All these issues highly influence the performance of the algorithm and results in premature convergence ultimately provide sub-optimal solution [19]. The lose of diversity is also a major issue related the premature convergence. Different modifications in the canonical PSO algorithm have been presented to over come the limitations. All these modified variants assure better performance and convergence profile but at the same instance induce an additional complexity in the standard algorithm.

The above context reveals that the PSO algorithm performance is highly influenced by the parameters used by algorithm itself. BBPSO algorithm takes the advantage over the other algorithm by minimizing the the parameter requirement and eliminate the velocity formula by directly updating the position by sampling the the search space using Gaussian distribution [20].The proposed work involves a enhanced BPSO variant by incorporating a Cauchy jump strategy with the standard BBPSO to avoid stagnation and premature convergence [21]

This dissertation work is organized in 6 chapters. In the succeeding chapter a detailed literature review of various papers related to FIR filter designing using various optimization techniques has been presented. Chapter 3 describe FIR high pass filter problem formulation part and constraint formulation have been present. Chapter 4 introduces the proposed BBPSO algorithm with sufficient mathematical background followed by comparison of results with other PSO variants is presented in chapter 5. Finally, Chapter 6 conclude the entire dissertation work. .

CHAPTER 2

LITERATURE SURVEY

The availability of high-end digital signal processors have provided an opportunity to design higher order filters to achieve more accurate filter specifications. While one the other higher order filter problem presents a great challenge due to high complexity, multi-model search space, multidimensional nature and non-linearity.Therefore it requires a more efficient and robust optimization technique. Various linear as well as non-linear design techniques have been presented in literature. Some of the important design techniques are described in the following literature survey:

Window techniques, frequency sampling, equi-ripple design techniques and weighted least square error are some of the conventional approaches. Window techniques is one of the most straightforward method for FIR filter designing. In this technique filter impulse response is convoluted with some window function. Different type of windows such Rectangular, Hamming, Hanning and Kaiser are used in order to reduce oscillatory behavior (Gibbs phenomena) [22]. All these windows convert the infinite impulse to finite impulse response. The choice of window depends directly on the filter specification [6]. The major limitation of this method is that it fails to control frequency response in various frequency bands as well as the transition width thus results in suboptimal solutions. [23].Frequency sampling is an another technique used for filter designing.It involves the sampling of frequency response at predefined equidistant points by using Discrete Fourier Transform. further the filter coefficients are calculated by using Inverse Discrete Fourier Transform.Batter control over the transition width can be achieved by this technique but the approximation error is zero only for the predefined frequency samples [6].

The conventional techniques fails to achieve feasible solutions when subjected to a complex multi-objective and constrained problem. Further these techniques require fine tuning of different parameters in order to provide faster convergence These facts are the deriving force towards the use of Meta-Heuristic optimization techniques. These techniques are inspired by either the social behavior of animals or the various natural phenomena [7]. Due to their effectiveness, efficiency and robustness these techniques are extensively used to solve real- world and complex problem. Several Meta-Heuristic optimization techniques have been devised over the recent past and the process of evolution of such techniques is still on [24]. There are several factors which have influenced the increase of such techniques for solving optimization problem form various disciplines. The very fist factor is the increased computational power which enables the complete utilization of these techniques in minimum possible time. Secondly the flexibility and ease in modification has produced a dynamic effect in the advancement of meta-heuristic techniques. These techniques are applied to single objective problems and then their application can be extended to multiple objective variant of the problem without much complexity.Thirdly the raising awareness about existence and importance of multi-objectives in various domains of science and technology in the recent past [25]. The Filter designing and optimization is also not an exception where the need of utilization of these techniques has not been felt. Various meta-heuristic techniques used for filter designing are Particle Swarm Optimization (PSO),Simulated Annealing,Genetic Algorithms (GA) Differential Evolution (DE), artificial Bee Algorithms, Tabu Search, Ant Colony Optimization (ACO),and Harmony Search [9, 11, 13, 17, 26, 27].

PSO [17] was explicated by Kennedy and Eberhart and it is a population based algorithm based on the social behavior of animals.This algorithm is found to be more robust for solving non-linear optimization problems as compared to other meta-heuristic techniques. PSO has become an algorithm of grater interest for different optimization techniques due to its ease in implementation and flexibility. Other advantages of PSO algorithm are simple concept,lower memory requirement, robustness, efficiency ,faster convergence and use of fewer parameters. Beside all these advantages some unresolved issues are also associated with PSO. Firstly it lacks in mathematical background . It is very newer technique as compares to other population based techniques. Secondly being an iterative technique it requires larger computation time as compared to convention mathematical approaches. Thirdly performance of algorithm is highly influenced by the population initialization and various parameters. Fourthly premature convergence due to homogeneity of particles and loss of diversity of population. Fifthly the stochastic nature of final solution due to the use of random numbers [28]. All these drawbacks ultimately results in suboptimal solutions.

To enhance the performance of PSO, various strategies have been adopted by various researchers to address the issues related with it. Some of the researchers worked on the particle initialization which is a vary first step of PSO algorithm.Since the performance of the algorithm is highly influenced by the initialization therefore an improper initialization may stuck the algorithm in local minima[29]. Nguyen et al [30] employed various low discrepancy sequences such as Halton, Sobol, and Faure for population initialization. Many benchmark functions were used to demonstrate the effect of initialization on the functioning of the PSO algorithm. Jabeen et al [31] intimated an opposition based population approach to avoid barren areas of search space. This algorithm uses one extra step to find an opposite population as compared to the standard PSO initialization.

Clerc [32] proposed the use of some constriction factor to put some limit on the undesired dynamic nature of particles in order to control their trajectories.The use of constriction factor helps in maintaining balance between the exploitation and exploration.The exploration of search space can be enhanced by using various coefficients in the velocity equation. The author also present a thorough analysis of particle trajectories as they move in the search space. The proposed modification are able to find the optimum solution to many complex benchmark functions.

Li [33]introduced inertial weights to improve the convergence of algorithm. The effectiveness of using exponentially decreasing inertial weights is evaluated on five different benchmark functions. A stochastic mutation of algorithm has also been used which prevent the algorithm to stuck with the suboptimal attractor.

Wang *et al.* [34] reported another variant of standard PSO which incorporate a mutation operator to avert the occurrence of local optima. The proposed algorithm combine a mutation strategy which incorporate global best information and two random numbers for the working. The alteration in the algorithm helps the trapped particle to jump form the local optimum positions. Various well established benchmark function are used to demonstrate the performance improvement caused by the mutation operator.

Kennedy [35] reported many topologies to enhance information sharing within the population for better performance of PSO algorithm.The author fond that the gbest topology causes a huge reduction in diversity of the population because the particles get attracted towards a common attractor. Hence the potential areas of search space may remain un-investigated and results in suboptimal solution.While on the other hand lbest topology has good exploration properties because many regions are explored in a parallel manner.Eventually it may provide better result as compared to gbest topology.The only drawback of lbest topology is that it requires more memory space. Many other custom topologies viz. star, pyramid, ring, and von-Neumann have also been discussed in the literature [36].

Kennedy [35] invented a new variant of PSO called as BBPSO.Despite the fact that some of the traditional features of PSO algorithm were vanished in this technique but it still outperform the basic PSO and its other variants.The deviation from the basic PSO algorithm basically lies in the two facts. Firstly, the use of velocity equation to update particle position was totally eliminated in this. Secondly it uses Gaussian sampling to explore the search space. The major advantage of BBPSO is that id do not use any parameters in position updating equation. Thus it eliminates the extra efforts required to fine tune various parameter as in the case of other algorithms. The simplicity and robustness of algorithm makes it an ideal choice for complex and multi-modal optimization problems.

Sharma S. *et al.* [37] demonstrated the use of DE optimization for design FIR filter. The filter design problem is devised as a multiple objective problem for optimization by incorporating the ripple constraint with the least squared Error approximation. The author uses a penalty based method to handle the constrained design problem.This work also present the performance comparison between constraint and unconstrained problem. Lesser number ripple with low and almost same magnitude were obtained in the stop band.

Mandal S. *et al.* [1] presented a paper on Particle Swarm Optimization by incorporating a Constriction Factor and Inertia Weight (PSO-CFIWA) approach to avoid stagnation. The modified variant of PSO was applied for designing high FIR filter.The limitations of premature convergence and stagnation in case of basic PSO algorithm are addressed by modifying the basic velocity equation with the introduction of of constriction and weight factor.The effectiveness of improved algorithm was demonstrated by implementing high-pass filters of different orders. GA and Parks and McClellan algorithm (PM) are used for performance comparison purpose. The proposed algorithm perform batter in term of accuracy and shows faster convergence.The filters designed by the proposed algorithm has higher stop band attenuation and smaller ripple. constricted transition band and more accurate frequency response are the other advantages ot the proposed design.

Aggarwal A. *et al.* [7] investigated the potential of various bio-Inspired swarm techniques for designing optimal FIR filter.The author conceived Cuckoo search, particle swarm and real-coded genetic for the given problem.Filter design problem is formulated as absolute error approximation. Two cases of filters having band stop band pass frequency response are considered in the study. The author also touched on the tedious task of parameter tuning of various algorithms and the dependency of these parameters on the performance. Lastly the author describe the CS algorithm as the best technique for filter designing due to its accuracy, minimum stop band and passband ripples, high attenuation in stop band and lowest execution time.

Saha S. *et al.* [38] inroduced an adaptive variant of the conventional PSO algorithm which uses Elitist Learning Strategy (ESE) for FIR filter designing.The use of ESE provide momentum to the particles an thus helps in maintaining a balance between the the exploitation and exploration properties of population. This modification involves the use of Gaussian distribution in. The performance efficiency of the proposed method has be illustrated by comparing the simulation results with canonical PSO and real coded genetic algorithm (RGA). Lastly the author comments on the faster convergence rate of APSO in comparison with conventional PSO and RGA.

Ababneh J.I. and Bataineh M.H. [39] studies PSO and GA for estimation of filter coefficients of a linear phase FIR filter by considering two different set of filter specifications. The first case takes into account the order of the filter, frequencies of passband and stopband , and the proportion of the passband and stopband ripples values. While the other case consider a viable stopband ripples and passband size with other predefined specifications. Author also demonstrated the consequence of quantization off the coefficients on the filter response in frequency domain. A comprehensive statical analysis of of various performance parameters has also been presented in the this work.

Kar R. [40] collaborated a craziness factor with the conventional PSO and employed the modified technique to FIR filter design.The craziness factor helps in maintaining the population diversity and hence prevent algorithm to stuck in the local minima. The FIR band stop filter is considered as a design problem.The author studied the improvement in performance by comparing the simulation results with that of conventional PSO, comprehensive learning particle swarm optimization (CLPSO) and Parks and McClellan (PM) Algorithm.An analysis of convergence of the proposed and the other algorithm has also been presented in the paper.

Boudjelaba K. *et al.* [41] studied the standard GA, AGA, PSO, NPSO and CPSO for designing low pass FIR filter. All these optimization techniques have been applied to the design of FIR filter of 30^{th} and 40^{th} order.The filter design problem is formulated as a weighted Least squares error.The various variants of both PSO and GA are employed and their performance is evaluated on the basis of statical analysis, convergence profile, and frequency response. The author also accented on the use of intelligence in the meta-heuristic techniques to make the algorithms more efficient by incorporating self - tuning strategies.

Karaboga N. and Cetinkaya B. [2] presented the potential of differential evolution (DE) algorithm for FIR filter designing problem. LMS error was used as the fitness function for the optimization problem. Three cases of 8^{th}, 14^{th} and 20^{th} order filter are considered in the paper. DE based method was found to be more suitable and relatively more fast as compared to GA based method for FIR filter designing . Convergence profiles of the two algorithm has also been presented to demonstrate the speed of convergence.

Chandra A. *et al.* [42] proposed an alternative multiplier-less hardware efficient design technique synthesized by using DE algorithm. The author also studied the effect of canonical signed digit representation on the complexity of filter. The CSD based approach was presented as an alternative mutation strategy other than conventional strategies.The simulation results obtained by the proposed designed technique were also validated on a FPGA platform.

Mondal S. [43] *et al* presented a novel approach which monitors inertial weights before updating them for designing Band - Pass FIR filter. The proposed technique tends to maintain a balance between the exploration and exploitation properties of population. This modification also helps in reduction of oscillatory behavior of particles and avoid the trapping of particles in local minima and provide better results as compared to the standard PSO. Various specifications such as filter order, passband and stop-band frequencies and feasible ripple size were considered.The performance comparison of the simulation results with other evolutionary techniques such as real coded GA, DE, and PM reveals the superiority of the proposed algorithm.

S. Shekhar *et al.* [44] presented BBPSO as an alternative techniques for designing FIR filter. The problem of filter design is formulated as a least squared approximation of the desired frequency response relative to the designed filter frequency response. Two cases of 20^{th} and 30^{th} order low pass filter were realized using BBPSO technique. The author also presented a comprehensive performance comparison of BBPSO and the standard PSO for filter design.The potency of the proposed technique was evaluated on the basis of minimum and maximum stop band attenuation and maximum pass band ripples, and stop band ripples, .

The significant advantages of linear phase, BIBO stability and low coefficient sensitivity makes FIR filters more suitable for many DSP applications. On the contrary side FIR filter implementation requires a large number of arithmetical calculations as required by their IIR counter-part. More number of arithmetical operations demands more power and results in slow speed. This fact has motivated the researchers towards the hardware efficient implementation. The lower power and hardware efficient design become very crucial when the filter are designed for portable devices like cell phones,tablets, laptops,wireless area networks, and other battery - operated devices. An extensive work has been done in the field and it is still a dynamic area of research [5]. Due to the low cost and higher speed of operation the fixed point digital signal processors are the ideal choice. These processors requires the filter coefficients to be realized in fixed point format rather than floating point. One of the simplest methods to realize finite word length FIR filter is obtained by rounding the optimum infinite precision coefficients to its predefined fixed bit representation. The direct rounding of the filter coefficients results in degraded filter response [45]. This effect is known as finite word-length effect. The degradation produced due to this effect can be minimized by considering this effect during the design phase to meet the arbitrary response specification.

Leban M. *et al.* [46] presented a paper on adaptive FIR designing. The problem is formulated as a weighted LSE subjected to finite word-length constraint. Standard

GA was used for the word-length optimization and it uses a fixed point implementation. The author also collaborate area and delay with the quantization error in the optimization criterion because of two reasons .Firstly a filter with too large area is impractical. Secondly the delay limit the higher frequency on which a filter can operate. Lastly the author establish GA as an efficient optimization technique for designing an adaptive echo-cancellation filter.

Hu X. *et al.* [47] presented an alternative algorithm for designing FIR filter with coefficients having variable precision. The proposed algorithm makes the use of the fact that coefficient sensitivity varies coefficient to coefficient. The highly sensitive coefficients uses a high precision while on the other hand less sensitive one use a lower precision. variable precision provides a significant reduction in redundancy which ultimately reduce complexity, and filter area over the uniform word-length implementation.

Soderstrand A. *et al.* [48] combined the a technique of trading adders for delay with the minimum adder CSD block technique for hardware reduction. The author has tried to minimize the error produced by the fixed number of bits by increasing the filter order. This method uses a exhaustive search for finding optimum solutions. The author used the proposed technique for approximation of "double-jump filter" which is used for FQPSK-KF modulator implementation. A comprehensive comparison of frequency response has also been provider between 6-bit and 24^{th} order and 24-bit and 6^{th} order filter. Nielsen J.J. presented a analytical analysis of sophisticated quantization procedures to provide a statical prediction of quantization effect on the frequency response.

Coath G and Halgamuge S.K [49] discussed various techniques for addressing constraints for PSO subjected to non-linear optimization problem. A abstractive survey of constraint handling methods for EA has also been presented. Dynamic multiple stage penalty functions and the preservation of viable solution methods were used to handle non-linear constraints. The performance of the proposed techniques was evaluated using various standard test function.The performance of the two techniques was established to be extremely competitive however the convergence rate of proposed approach was detected to be much faster as compared to feasible solution approach. Finally the author also comments about the applicability of proposed techniques for many real-world optimization problems.

CHAPTER 3

PROBLEM DEFINITION

The impulse response of an ideal filter is non-causal and infinite. Therefore it can not be realized practically. Hence there is a need to approximate the ideal filter response with finite number of filter coefficients. The main objective of the any optimization technique in the filter designing domain is to estimate a set of filter coefficients to meet the desired specifications.

A digital FIR filter in Z domain is characterized by,

$$H(Z) = \sum_{n=0}^{N} h(n)Z^{-n}; \qquad n = 0, 1, \cdots, N \tag{3.1}$$

where $h(n)$ is the finite impulse response and N is the order of the filter having length $(N + 1)$.Depending on the length and type of symmetry four type of FIR filter are categorized in four types namely Type 1, Type 2, Type 3 and Type 4. This study uses type 1 filter having odd length and satisfies even symmetry i.e $h(n) = h(N - n)$ for $0 \leq n \leq N$.Type 1 filters are preferred over the other filter due to their versatility[6] in the usage. The property of symmetry also reduce the computational task by a factor of 2 . This means that instead of N only $\frac{N}{2} + 1$ filter coefficient are requires to be optimized.The rest of coefficients can be find by using the symmetry property.

In order to satisfy frequency domain specifications the filter needs to be represented in the frequency domain. The normalized frequency response of the FIR digital filter can be estimated by taking the Discrete Fourier Transform (DFT) of the impulse response at finite number of frequency samples in $[0, \pi]$ interval by:

$$H(e^{j\omega_k}) = \sum_{n=0}^{N} h(n)e^{-j\omega_k n} \tag{3.2}$$

where, $\omega_k = \frac{2\pi k}{n}$is the k_{th} frequency sample and $H(e^{j\omega_k})$ represents the a complex vector in frequency domain.

The very first step in designing an optimum filter is to characterize the filter design problem as an optimization problem with an objective to minimize an error function. The deviation in frequency response of designed filter from the desired response is treated as an error function by many researchers. Further various specifications can also be incorporated with LSE to form a constrained optimization problem. Maximum ripple magnitude is phrased as a constraint to the FIR design problem The non-linear constrained optimization problem can be solved by using either direct or indirect constraint handling methods. Indirect methods explicitly convert a constrained problem to an unconstrained problem and are easier to implement. The LSE and the maximum ripple constraints has been formulated in the following sub-sections.

3.1 Least Squared Error

Several kind of error fitness functions have been used by researchers in the present literature such as least squared error, absolute error, squared absolute error and integrated least squared error. But LSE is the on of the most exercised error fitness function for the filter design problem. It is basically the squared error between the desired frequency response and the designed frequency response This error function is the objective function of the filter design problem .The filter design problem is constructed as a minimization problem.The main objective of the algorithm is to find an optimum set of filter coefficients in order to minimize the

$$E = min \sum_{k=1}^{K} |H_i(e^{j\omega_k}) - H_d(e^{j\omega_k})|^2 \tag{3.3}$$

where, E is the squared deviation from the ideal response and H_i defines the ideal filter magnitude response given as:

$$H_i(e^{j\omega_k}) = \begin{cases} 1 & \text{for } \omega \in passband \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

3.2 Constraints

Various filter specifications can be incorporated with the LSE as constraints to the filter design problem. The passband ripple, stop band ripples and Finite word length are the three constraints which have been considered in this work. The passband

and stop band ripple constraint helps in providing a flatter frequency response. Finite word-length constraint introduces the hardware limitation in the design problem thus cause reduction in the finite word length effect caused by rounding off the filter coefficients to a finite number of bits.

3.2.1 Ripple constraint

Ripple are the undesired fluctuations in the filter magnitude response and it is one of the most critical parameter for evaluation of the filter performance. Due the causal nature of the digital filters ripples are inherent because there is no frequency band having zero magnitude response. The ripple constraint is formulated as the maximum ripple magnitude in both pass band and stop band as:

$$\delta_1(\omega) = \begin{cases} max(|H_d(e^{j\omega_k})|) & \text{for } 0 \leq \omega \leq \omega_c \\ max(|1 - H_d(e^{j\omega_k})|) & \text{for } \omega \geq \omega_c \end{cases} \tag{3.5}$$

3.2.2 Finite Word Length Constraint

Fixed point implementation is most commonly used when a critical hardware efficient design of digital filter is required. Since the multipliers are the most complex elements of any digital filter therefore they need to be kept simple. These multipliers are nothing but the filter coefficients. The complexity of the filter can be reduced by using minimum word-length coefficients. The precision of the filter coefficient is directly related to the filter performance. Also direct rounding- off of filter coefficients in not possible because different coefficient have different sensitivities towards the filter magnitude response. This fact makes the finite word-length effect to be treated critically during the very initial design stages. Rather than using complex and specific methods to reduce finite word-length effect it is advantageous to subject it as constraint to the optimization problem. The finite word length effect is formulated as the absolute error between the magnitude response of filter with floating point coefficients and the magnitude response of filter with fixed poin coefficients[**?**].

$$\delta_2(\omega) = |H_{float}(e^{j\omega_k})| - |H_{fixed}(e^{j\omega_k})| \tag{3.6}$$

CHAPTER 4

BBPSO ALGORITHM

4.1 Particle Swarm Optimization

Kennedy and Eberhart set a new benchmark in the world of optimization by introducing a new swarm-intelligence based meta-heuristic optimization algorithm called as Particle Swarm Optimization (PSO).This optimization technique is based on the social behavior of animals such as bird flock and school of fish. Simplicity and ease in the implementation are the major attractions of this algorithm. The whole paradigm can be implemented with a few lines of a computer code without requiring too much memory and processing power. The working principle of this algorithm lies in the fact that the particles aviate in a space having multidimensional nature and store their personal best location and global best locations to find the optimum solution by an iterative process. The velocity and position of each particle in the swarm is governed by following equation:

In PSO each membered of the swarm is dealt as a mass-less and volume-less "particle" or a "point" and their position is represented by a vector $X_i = (X_{i1}, X_{i2} \cdots X_{in})$. Each vector X_i is a possible solution. All these particles are free to move in n-dimensional space under the influence of the global best $X_{gbest} = (X_{gbest_1}, X_{gbest_2} \cdots X_{gbest_n})$ and personal best $X_{lbest_i} = (X_{lbest_{i1}}, X_{lbest_{i2}} \cdots) X_{lbest_{id}})$.The position of particles is altered by providing some velocity $V_i = (V_{i1}, V_{i2} \cdots V_{id})$.The magnitude and direction of velocity depends on the deviation of particle from the X_{gbest} and X_{lbest_i}.

$$V_{ij}^{k+1} = w * V_{ij}^{k} + C_1 * r_1 * (X_{lbest_{ij}}^{k} - X_{ij}^{k}) + C_2 * r_2 * (X_{gbest_j}^{k} - X_{ij}^{k}) \tag{4.1}$$

$$X_{ij}^{k+1} = X_{ij}^{k} + V_{ij}^{k+1} \tag{4.2}$$

where $w \in [0.3, 0.85]$ is the inertia weight. C_1 and C_2 are constants known as cognitive and social constant respectively. r_2 and r_1 are randomly generated numbers $\in [0, 1]$. k

Figure 4-1: Bird flocking

Figure 4-2: School of fish

signifies the present epoch. To restraint the particle to the specified search space V_{max} and V_{min} limits are also imposed on the velocity of particles.The PSO pseudo-code for PSO is presented in Algorithm 1.

Algorithm 1 Psudocode for PSO algorithm

```
Input: swarm size P, Dimensions D, $\omega$, $C_1$,$C_2$, maximum bound $x_{max}$, minimum
  bound $x_{min}$
  Initialize each particle $X_{ij}$ using uniform probability distribution in $[x_{min}, x_{max}]$
  for $i = 1 \rightarrow P$ do
    for $j = 1 \rightarrow D$ do
      $X_{ij} = [x_{min} + (x_{max} - x_{min}) * U(0,1)$
      $X_{lbest_i} = X_i$
    end for
    Evaluate fitness $f(X_{ij})$ $X_{gbest} = min(X_{ij})$
  end for
  for $i = 1 \rightarrow i_{max}$ do
    Update the velocity $V_i$ according to equation (4.1)
    $X_i$ is updated according to equation (4.2)
    if $f(X_i) < f(X_{lbest_i})$ then
      $X_i = X_{lbest_i}$
    end if
    if $f(X_i) < f(X_{gbest_i})$ then
      $X_i = X_{gbest_i}$
    end if
  end for
Output: $X_{gbest}$
```

4.2 Bare Bones Particle Swarm Optimization

BBPSO was developed by Kennedy as a Gaussian variant of the standard PSO. An implementation of this technique is provided in Algorithm 2. It also eliminate the requirement of velocity equation by directly estimating the position. This study not only presents the aspect of center of oscillation but also the variability in the deviation from the center. This algorithm uses Gaussian distribution to sample the search space instead of uniform distribution used by other PSO variants. On the other hand BBPSO also decimate the use of various control parameters such as inertial weights and constriction factors. Thus it seems to be a parameter free algorithm which update the positions of particles given by:

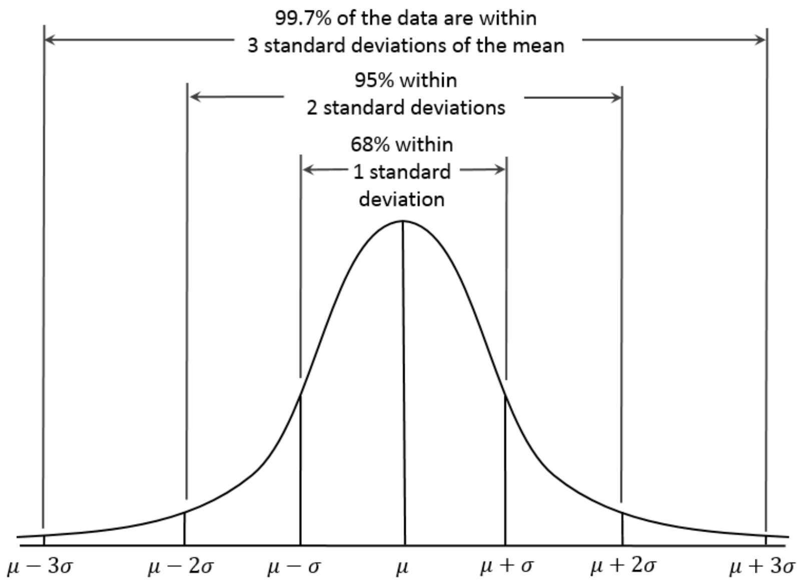

Figure 4-3: Gaussian Distribution

$$X_{ij}^{t+1} = G(\mu, \sigma) \tag{4.3}$$

Where G is a set numbers having Gaussian distributed centered around the mean (μ) of *Globle* and *local best* values whereas σ is absolute deviation of local best from the global best.

$$\mu = 0.5(X_{gbest_j} + X_{lbest_{ij}}); \tag{4.4}$$

$$\sigma = |X_{gbest_j} - X_{lbest_{ij}|}; \tag{4.5}$$

4.3 BBPSO with Cauchy jumps

Krohling *et al.* [21] presented a jump strategy to avoid stagnation and premature convergence in BBPSO algorithm. This jump strategy provide a mean by which particles can escape from the sub-optimal position when there is no improvement in the fitness. Gaussian and Cauchy probability distribution has been used to implement this strategy.The complete pseudo-code for BBPSO with jump strategy has been shown in the Algorithm 3.

The dynamics of the particles are prevailed by two driving forces. In the 1st case, if there is an amelioration in the fitness value over iteration to iteration, the particles are

Algorithm 2 Psudocode for BBPSO algorithm

```
Input: swarm size P, Dimensions D, maximum bound $x_{max}$, minimum bound $x_{min}$
  Initialize each particle $X_{ij}$ using uniform probability distribution in $[x_{min}, x_{max}]$
  for $i = 1 \rightarrow P$ do
    for $j = 1 \rightarrow D$ do
      $X_{ij} = [x_{min} + (x_{max} - x_{min}) * U(0, 1)$
      $X_{lbest_i} = X_i$
    end for
    Evaluate fitness $f(X_{ij})$ $X_{gbest} = min(X_{ij})$
  end for
  for $i = 1 \rightarrow i_{max}$ do
    $X_i$ is updated according to equation 4.3
    if $f(X_i) < f(X_{lbest_i})$ then
      $X_i = X_{lbest_i}$
    end if
    if $f(X_i) < f(X_{gbest_i})$ then
      $X_i = X_{gbest_i}$
    end if
  end for
Output: $X_{gbest}$
```

then sampled in consistent with equation 4.3, while in the second case, when there's no amelioration in fitness over a number of iterations, then the particles are said to be stagnated. Therefore, stagnated particles ought to move according to another regime having better dynamics. The introduction of a jump strategy in such cases, permits fresh locations to be sampled, it may help to aviate from native attractors. this is done by incorporating a stagnation interval, that supervise the fitness value for every particle for a prefixed count of iterations

No improvement in fitness value causes a increase in the stagnation interval by one in each iteration. This process goes on until the stagnation interval reaches a predefined maximum stagnation interval and the particle is ought to jump to a new position. This jump strategy is implemented by using two mutation operators namely Gaussian and Cauchy which are commonly used with GA. During the stagnation interval the position of particle is calculated using following equation 4.7 or 4.6.

$$X_{ij}^{t+1} = P_{best} * \eta * N(0, 1) \tag{4.6}$$

$$X_{ij}^{t+1} = P_{best} * \eta * C(0, 1) \tag{4.7}$$

Where η is a the scaling factor, C(0,1) and N(0,1) are the random nubers generated using Cauchy and Gaussian distributionin ∈ [0,1].

Algorithm 3 Psudocode for BBPSO with Cauchy Jumps algorithm

```
Input: swarm size P, Dimensions D, maximum bound $x_{max}$, minimum bound $x_{min}$, scaling factor $\eta$
  Initialize each particle $X_{ij}$ using uniform probability distribution in $[x_{min}, x_{max}]$
  for $i = 1 \rightarrow\ P$ do
    for $j = 1 \rightarrow\ D$ do
      $X_{ij} = [x_{min} + (x_{max} - x_{min}) * U(0,1)$
      $X_{lbest_i} = X_i$
    end for
    Evaluate fitness $f(X_{ij})$ $X_{gbest} = min(X_{ij})$
  end for
  for $i = 1 \rightarrow\ i_{max}$ do
    if stagmation interval $\geq$ maximum stagnation interval then
      $X_i$ is modified according to equation 4.3
    else
      $X_i$ is modified according to equation 4.7
      stagnation interval[i]=0 // reset after a jump
    end if
    if $f(X_i) < f(X_{lbest_i})$ then
      $X_i = X_{lbest_i}$
    else
      stagnation interval++
    end if
    if $f(X_i) < f(X_{gbest_i})$ then
      $X_i = X_{gbest_i}$
    end if
  end for
Output: $X_{gbest}$
```

CHAPTER 5

SOLUTION APPROACH

5.1 Test Functions

BBPSO with Jump strategy has been first evaluated on various both type of benchmark functions namely unimodal and multi-modal. These benchmarks provides a comprehensive analysis of any algorithm because these functions are highly nonlinear and has a very complex search space. Therefor it is always advantageous to use these functions for performance analysis before applying the algorithm to the actual problem. All these functions have been framed as a minimization problem. A list of renowned benchmark function used for in optimization has been presented in Table 5.1 and 5.2. Table **??** shows the global minima values and corresponding ranges of variables. Comparison of proposed algorithm with standard PSO and BBPSO algorithm has also been present.

Table 5.1: Global optimum and range values of different unimodal test functions

S.No.	Expression	Range	x_{max}	Global Optimum
1	$\sum_{i=1}^{n} x_i^2$	$[-200, 200]$	200	0
2	$\sum_{i=1}^{n} [100(x_{i+1} - x_i)^2 + (x_i - 1)^2]$	$[-20, 20]$	20	0
3	$\sum_{i=1}^{n} i x_i^2$	$[-10, 10]$	10	0
4	$\sum_{i=1}^{n} \mid x_i \mid + \prod_{i=1}^{n} \mid x_i \mid$	$[-50, 50]$	50	0
5	$exp(0.5 \sum_{i=1}^{n} x_i^2) - 1$	$[-50, 50]$	0	0

5.2 Experimental setup

All codes have been written in MATLAB script 8.03 version executed on intel core (TM) i5 processor, 2:10 GHz with 2 GB RAM system running on Windows 7 operating

Table 5.2: Global optimum values of different test functions

Test function	expression	global optimum
Rastrigin function	$\frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	0
Griewank function	$\sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	0
Ackley function	$-20\exp\Bigg(- 0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\Bigg) - exp\Bigg(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\Bigg) + 20 + e$	0

Table 5.3: Parameters used by different algorithms

Parameter	BBPSO	PSO	BBPSOWCJ
w	–	$[0.3, 0.85]$	–
c_1	–	.5	–
c_2	–	.5	–
X_{min}	-5	-5	-5
X_{max}	5	5	5
V_{min}	–	.02	–
V_{max}	–	1	–
p_{size}	30	30	30
(it_{max})	1000	1000	1000
scaling factor η	–	–	2

system. Various parameters used by the algorithms have been listed in the Table 5.3. All experiments are executed for 50 runs while using 1000 epochs in every run to have a good statical analysis of each algorithm.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 Performance analysis based on standard test functions

The performance of the three techniques has been tested by evaluating these techniques against various test function. Table 6.1 and Table 6.2 demonstrate a comprehensive performance comparison of BBPSOWCJ with basic PSO and BBPSO for unimodal and multi modal test functions respectively in terms of best fitness value for multiple trials. Various parameters such as population size, maximum number of iterations, control constants and number of trails have been kept same for all techniques for the evaluation. Every techniques has been evaluated for a maximum of 100 trial for better efficiency and robustness analysis. Table 6.1 shows that the unimodal test function have a less complex search space and the performance off all the algorithms is quiet satisfactory for these test function. On the other hand multi-modal test function have a complex search space and a number of minima points. Therefore these functions present a great challenge for the optimization techniques as compared to unimodal test functions. The simulation results shows that the jump strategy works well in avoiding suboptimal solution to the complex optimization problem as compared to the standard BBPSO and PSO techniques. It can also be inferred form the results that the performance improvement is directly related to the enhanced exploring properties of the proposed technique due to jump strategy.

Table 6.1: Best fitness values of unimodal test functions

Function	PSO	BBPSO	BBPSOWCJ
F_1	$5.629E-12$	$4.081E-24$	$7.46E-28$
F_2	3.04	0.0231	$3.92E-6$
F_3	$5.920E-15$	$1.4638E-16$	$3.6E-21$
F_4	$3.462E-8$	$4.251E-21$	$9.46E-24$
F_5	$17.454E-12$	$5.467E-27$	$6.247E-32$

Table 6.2: Best fitness values of multimodal test functions

Function name	PSO	BBPSO	BBPSOWCJ
Ackley function	13.682	$6.693E-10$	$9E-13$
Rastrigin function	5.348	1.5430	0.732
Griewank function	2.3125	1.892	$6.382E-4$

Figure 6-1: 20^{th} order filter magnitude (db) response

6.2 Analysis of magnitude response

The proposed technique along standard PSO and BBPSO has been used for designing high pass and low-pass type of filters. Further two cases of 20 and 30 order for each filter type have been considered in order to analyse the robustness of the three techniques. Figure 6-3 and 6.4 shows the lowpass filter response for 20^{th} and 30^{th} order filter respectively. While figure 6-1 and 6-2 shows normalized high pass filter response. The normalized frequency response reveals the superiority of the proposed technique over the standard techniques for both the cases of high pass and low pass filter designing.

Table 6.3: various performance parameters of designed 30^{th} order filter

specification	PSO	BBPSO	BBPSOWCJ
Maximum pass band ripple (normalized)	0.03533	0.01713	0.0145
Maximum stop band ripple (normalized)	0.0942	0.0671	0.048
Peak pass band ripple (α_p)	0.3124	0.1500	0.126
Minimum stop band attenuation (α_s)	$17.5189dB$	$23.4655dB$	$22.6dB$
Maximum stop band attenuation	$64.39dB$	75.43dB	$105.5dB$

Table 6.4: Filter coefficients for 30^{th} order low pass FIR filter

PSO	BBPSO	BBPSOWCJ
0.0039	0.0078	0
-0.0234	-0.0273	0.0117
0.0195	0.0195	-0.0117
0.0078	0.0078	-0.0156
-0.0195	-0.0195	0.0313
-0.0078	-0.0078	0.0078
0.0273	0.0273	-0.0391
0.0078	0.0273	0.0039
-0.0391	-0.0586	0.043
-0.0078	-0.0078	-0.0117
0.0586	0.0586	-0.0352
0.0117	0.0117	-0.0039
-0.1016	-0.1055	0.0977
-0.0117	-0.0195	0.0117
0.3164	0.3203	-0.3203
0.5117	0.5117	-0.5078

Figure 6-2: 30^{th} order filter magnitude response(dB)

Figure 6-3: 20^{th} order low pass filter magnitude (dB) response

Figure 6-4: 30^{th} order low pass filter magnitude (dB) response

Table 6.5: 20^{th} order low pass filter coefficients

PSO	BBPSO	BBPSOWCJ
-0.0858	0.0844	-0.0442
0.0195	-0.0697	0.0194
0.0136	-0.0112	0.0117
-0.0386	0.0232	-0.0324
-0.0074	0.0120	-0.0123
0.0552	-0.0538	0.0543
0.0138	-0.0130	0.0125
-0.1073	0.1005	-0.1003
-0.0116	0.0130	-0.0128
0.3189	-0.3168	0.3162
0.5106	-0.5125	0.5132

Table 6.6: 20^{th} order high pass filter coefficients

PSO	BBPSO	BBPSOWCJ
-0.0007	0.0396	-0.0137
0.0417	-0.0421	0.0198
0.0416	-0.0419	0.0124
-0.0502	0.0499	-0.0323
-0.0440	0.0439	-0.0121
0.0674	-0.0674	0.0538
0.0469	-0.0467	0.012
-0.1080	0.1082	-0.1008
-0.0479	0.0483	-0.0132
0.3193	-0.3188	0.3163
-0.4511	0.4516	0.3163

CHAPTER 7

CASE STUDY: ECG SIGNAL DENOISING

Filters are the frequency selective devices. Basic operation performed by a filters are manipulation of a raw signal, extraction of useful signal from a wide spectrum of frequencies and reshaping of signal. A digital filter is may be a specialized digital signal processor or a software routine running on a personal computer. Basically a digital signal is a hardware or software which perform convolution operation on a signal having discrete time and discrete amplitude.The digital filter are more advantageous over their analog counterpart because of their ease in implementation, flexibility, compact size, re-programmability and high accuracy. Another advantage of the these filters is that they can filter both real-time as well as stored signals.

7.1 Application of digital filters

The application area of digital filter is very wide spread ranging from communication, imaging, biomedical and, data instrumentation to data acquisition. Some of the common application of digital filters are:

1. Noise suppression: Digital filters are used for noise suppressing of various signals.
2. Enhancement of frequency spectrum: For signal equalization of edge detection in images.
3. Attenuation or removal of undesired frequency ranges: Such DC component removal and attenuation of any specific frequency.
4. Bandwidth limitation: As anti-aliasing filters for sampling and for ensuring the frequency allocation to any transmitted signal
5. Other operations: Filters may be used for other special functions such as differentiator, integration and various transformations.

7.2 ECG signal

Electrocardiogram (ECG) signal (figure 7-1) are one of the most important biomedical signals. These signals represent the electrical activity of heart. Due to very small magnitude these signals are highly pron to noise. The main sources of noise are power line, interference due to electrical machinery, electrode contact noise, equipment noise and artifacts. There for it requires digital filtration before storage or display.

Figure 7-1: ECG waveform

7.3 Various noise sources in ECG signal

1. Interference due to nearby power-lines.
2. Contraction of muscles.
3. Artifacts resulting from motion of the subject.
4. Contact noise of electrodes.
5. Noise from other devises.
6. Wandering of base-line

7.4 ECG signal database

The present work uses MIT-BIH Arrhythmia Database [50] provided by Physionet. beside the signal this database also contain a header text file, a binary file and an annotated file. The text file contains auxiliary information such as number of electrodes, sampling rate, and data type. The database contains 48 records; each record contains data up to 30 minutes approximately. Each recorded at 360 Hz sampling frequency. with a resolution of 11 bits.

7.5 Application of designed filter for ECG denoising

The effectiveness of proposed design technique for FIR filter designing has been illustrated by the application of designed filter for ECG signal denoising.The proposed optimum fixed point implementation can be helpful for low cost hardware for real time applications.

7.5.1 Design parameters ot filter

Various filter specifications for ECG signal denoising are given in the Table

S.No	Parameter	Value of parameter
1.	Filter order	30
2.	Type	Lowpass FIR
3.	Cut-off frequency	150 Hz
4.	Sampling frequency	360 Hz

Table 7.1: Filter specifications for ECG signal

Table 7.2: Performance parameters

Parameter	Value
SNR	$13.8dB$
PSD (raw signal)	70
PSD (Filtered signal)	58

The performance of the designed filter is evaluated in terms of signal to noise ratio and the total power spectrum density. The results shows a reduction of 16dB in PSD and filter signal have a SNR value of 13.8db.

Figure 7-2: Noisy ECG waveform

Figure 7-3: Filtered ECG signal

CHAPTER 8

CONCLUSION

In this work an efficient technique based on BBPSOWCJ algorithm with maximum ripple and finite word length constraint is discussed for designing optimum and hardware efficient high pass and low pass FIR filter. From the simulation results it can be concluded that the frequency response of BBPSO filter with ripple constraint is comparable with the results derived using unconstrained BBPSO and other PSO variants.Thus because of its faster convergence and minimum dependency on control parameters, BBPSO optimization algorithm with ripple constraint can be utilized efficiently as an alternative of other PSO variants for FIR filter designing and optimization as an alternative of other PSO variants. A practical problem of filtering for ECG signal has also been discussed for performance analysis of the designed filter. In future more promising results can be obtained by increasing the number of trials and incorporating other filter specifications as constraints to the optimization problem.

PUBLICATION

1. Inderjeet Singh and Nirbhowjap Singh "Optimal Linear Phase FIR Filter Design using Bare Bones Particle Swarm Optimization (BBPSO) with Ripple Constraint", Advanced Computational Methods In Electrical Engineering,(SLIET) Sangrur,Volume 4, Issue 15.

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