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Hybridization of BBO-PSO for the designing of FIR filter

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ABSTRACT

This research article studies the performance of three metaheuristics processes: Particle Swarm Optimization (PSO), Biogeography Based Optimization (BBO) and Hybrid BBO_PSO approach for FIR filter design. The three approaches employ different strategies and computational effort to find a solution to a given objective function. BBO is more recently proposed population-based search method than PSO. Some researchers believed in the convergence superiority of BBO over the PSO and approved it due to its capacity to solve complex problems due to its ease of implementation. In this paper, for FIR filter design PSO, BBO and BBO_PSO schemes are compared. BBO_PSO generally outperform standard PSO and BBO schemes. The study also underlines the importance of introducing hybridization of two heuristics optimizations to make them more efficient. Furthermore, it establishes the potential complementary of the approaches while solving this optimization problem.

Keywords: *FIR filters, Particle swarm optimization, Biogeography-based optimization, Finite impulse response (FIR) filter*

1. INTRODUCTION

This paper presents investigational studies in Biogeography-based optimisation (BBO) and Particle swarm optimization (PSO) and their use in optimal designing of Finite impulse response (FIR) Filter [1]. In recent years, due to advancement in computer technology, field of digital signal processing is increasing. As a result design of digital filters is receiving great deal of interest. Digital filters are used in numerous applications from control system, communication system to system of medical applications. Digital filters are broadly classified into two groups, i.e., finite impulse response (FIR) filter and infinite impulse response (IIR) filter. In case of FIR filter response due to an impulse input will decay within a finite time and is a non-recursive filter whereas for IIR filter, impulse response never dies out. IIR filters are recursive in nature. Due to stability and linear phase FIR filters are preferred over IIR filter. IIR filters are fast as compared to FIR filter but practical implementation of FIR is simple as compared to IIR filters. FIR filters are preferred for easy design and stability. Traditionally different techniques exist for the design of FIR filter and its implementation such as window design, frequency sampling, weighted least squares design or equiripple design. Out of these, windowing method is the most popular. In this method, ideal impulse response is multiplied with a window function. There are various kinds of window functions (Butterworth, Chebyshev, Kaiser Etc.), depending on the requirements of ripples on the pass band and stop band, stopband attenuation and the transition width. The complexity of the design reaches the limit of conventional design approaches that prove unable to handle all the constraints of filter performances. While the science of digital filter design is well established, there are no conventional design procedures that lead to optimal design. For these reasons, design of FIR filters is an intensively researched area, aiming at obtaining more general and innovative techniques that are able to tackle new and complex engineering problems of great relevance today. Therefore heuristic tools such as evolutionary computation, simulated annealing, tabu search, particle swarm optimization or biogeography-based optimization are employed in the design of digital filters to design with better parameter control and to better approximate the ideal filter. In further advancement and for better result hybrid model is used in which more than one optimizations are used simultaneously. In this PSO and BIBO are used simultaneously to design FIR filter.

1.1 Biogeography based optimization (BBO)

The science of biogeography and derived optimization technique is discussed. BBO has two major operators, i.e. migration and mutation. Researchers have further proposed variant with the objective of improving performance. This chapter dedicated to all the variants of BBO and the algorithmic flow of these variants.

Biogeography and BBO terminology

BBO is one of the recently developed population-based algorithms which has shown impressive performance over other Evolutionary Algorithms (EAs). As the name suggests, BBO is population-based global optimization technique developed on the basis of the science of biogeography, i.e., the study of the distribution of animals and plants among different habitats over time and space. BBO results presented by researchers are better than other optimization techniques like Ant Colony Optimization, Particle swarm Optimization, Genetic Algorithm and Simulated Annealing.

Originally, biogeography was studied by Alfred Wallace and Charles Darwin mainly as a descriptive study. However, in 1967, the work carried out by the MacAurthur and Wilson changed this viewpoint and proposed a mathematical model for biogeography and made it feasible to predict the number of species in a habitat.

BBO Terminology

Habitat: The habitat is an island that geographically isolated from other islands. Therefore, we use generic term habitat in place of the island. In the science of biogeography, a habitat is an ecological area that is inhabited or covered by particular plants or animal species. The candidate solutions for the problem, in BBO, are encoded as string as given by (1) and termed as habitats.

$$H = [SIV_1,\ SIV_2,\ SIV_3, \dots\dots\dots, SIV_M] \quad (1)$$

Habitat Suitability Index (HSI): HSI is a measure of the goodness or the fitness of the solution which is represented as habitat. Some habitats are more suitable for habitation than others.

Suitability Index variable (SIVs): Habitability is related to constituent factors of a habitat such as rainfall, temperature, diversity of vegetation etc. In BBO, there are parameters or variables encoded in a string format to make habitats.

Migration: Migration is a movement of species from one island or habitat to other for better comforts of living. In BBO, immigration and emigration terms are used related to migration of species from one island to other. Immigration is the act of species passing or coming into a country for the purpose of permanent residence or in other words, immigration is a replacement of an old solution feature in an individual with new solution feature from another individual. The solution feature comes from the contributing individual by way of emigration, whereas, Emigration is the act of species moving out of a home country or in other words, the sharing of a solution feature in BBO from one individual to another. The emigrating solution feature remains in the emigrating individual.

1.2 Particle Swarm Optimization

The PSO method is a member of the broad category of Swarm Intelligence methods and is based on the collaboration between individuals often called particles. In a PSO algorithm, each particle is a candidate solution equivalent to a point in n-dimensional space. The algorithm is generally randomly initialized, and the particles (candidate solutions) are placed randomly in the search space of the objective function. The PSO successfully leads to a global optimum. The main concept of PSO is that the potential solutions are accelerated towards the best solution. The particles iteratively evaluate the fitness of the candidate solutions and remember the location where they had best fitness value at each iteration the particles move taking into account their best position but also the best position of their neighbour. The goal is to modify their trajectory so that they approach as close as possible to the optimum. This optimum is achieved by an iterative procedure based on the process of movement and intelligence in an evolutionary system. PSO focuses on cooperation rather than competition, and there is no selection (at least in basic version), the idea being that even a poor particle deserves to be preserved, perhaps because i is the one which insures the success in the future, precisely because it is unusual. It doesn't require Gradient information of the objective function being considered, only its values. According to some results, PSO doesn't suffer from the problems encountered by other evolutionary Computation techniques.

2. EXPERIMENTAL SETUP

In this paper, 36-filter length FIR filter is optimized for minimum error between practical and ideal filter design. Average of 10 Monte-Carlo evolutionary runs is shown for PSO, BBO and Hybrid BBO_PSO for FIR filter design.

The parameters used in experiments are:

i. No. of Habitats or population: NP = 100
ii. Generations: 100
iii. No. of SIVs per habitat: 36
iv. Mutation range: ±1%
v. Maximum migration rates E = 1 and I = 1

3. RESULTS

In this paper the result of PSO, BBO and hybrid BBO_PSO is taken in terms of convergence performance, filter response and error

3.1 convergence performance

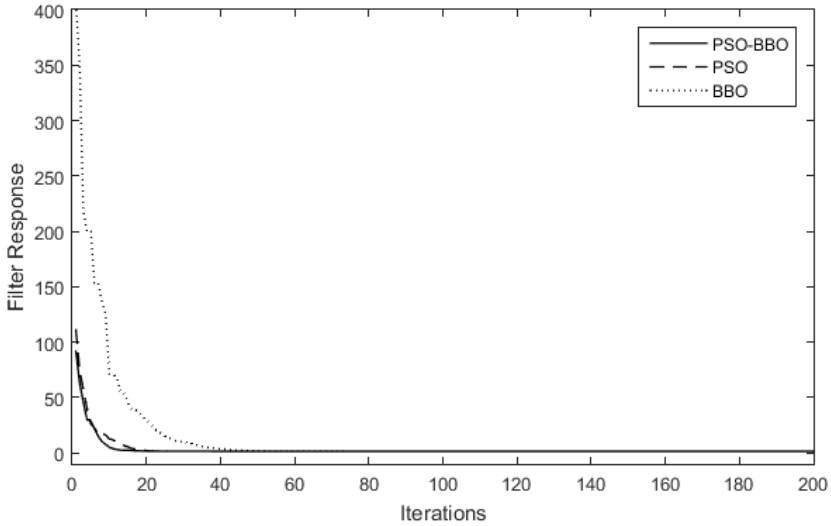

Fig. 1: Combined Convergence Performance

Combined convergence performance of FIR filter response shows that hybrid BBO_PSO performs better than BBO and PSO.

3.2 FIR Filter Design

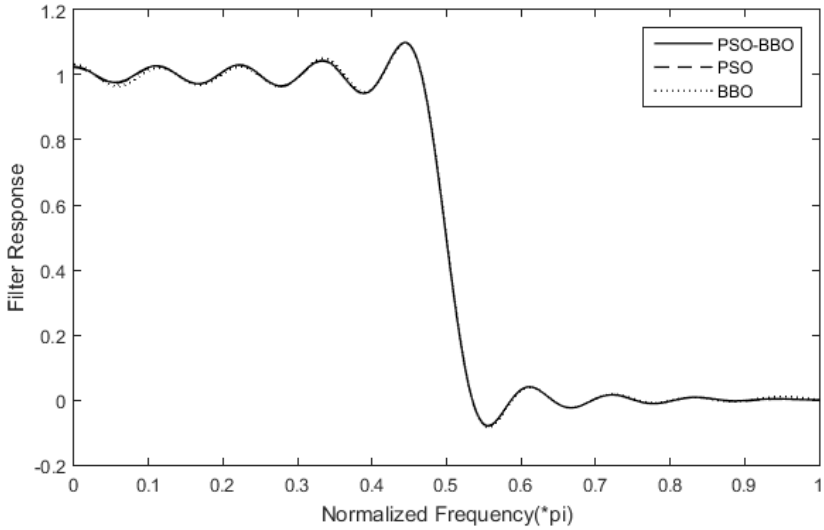

Fig. 2: Combined Filter Response

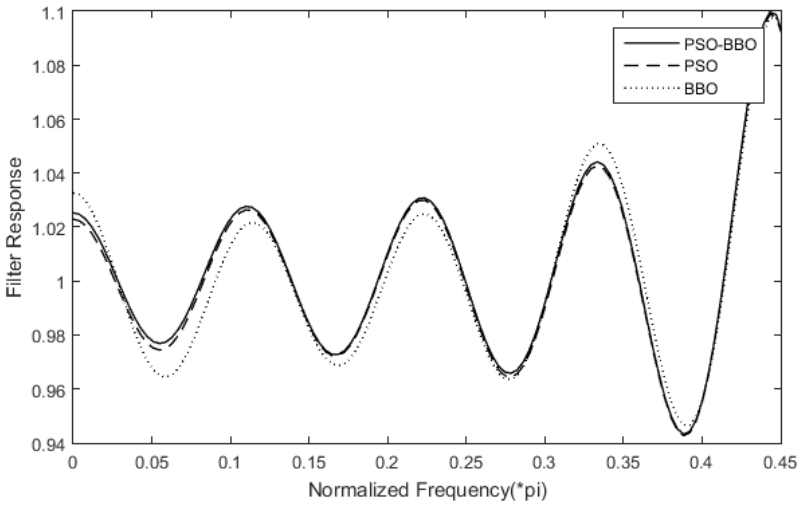

Fig. 3: Combined Filter Response (ZOOM)

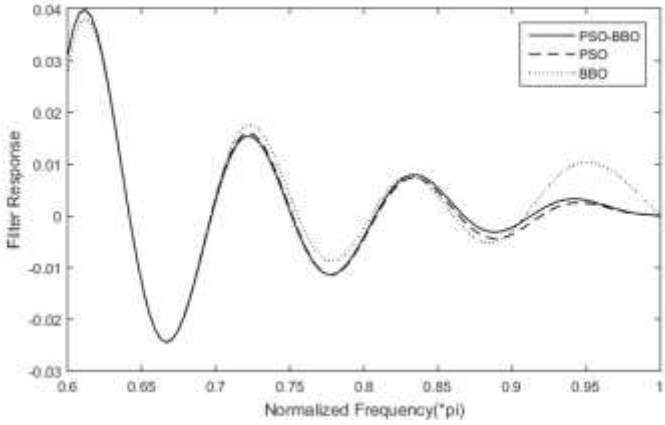

Fig. 4: Combined Filter Response (ZOOM)

In fig.2, fig.3 and fig.4, BBO_PSO shows the best filter response among the optimization techniques.

3.3 L1 Error

L1=Ideal filter response- Practical filter response

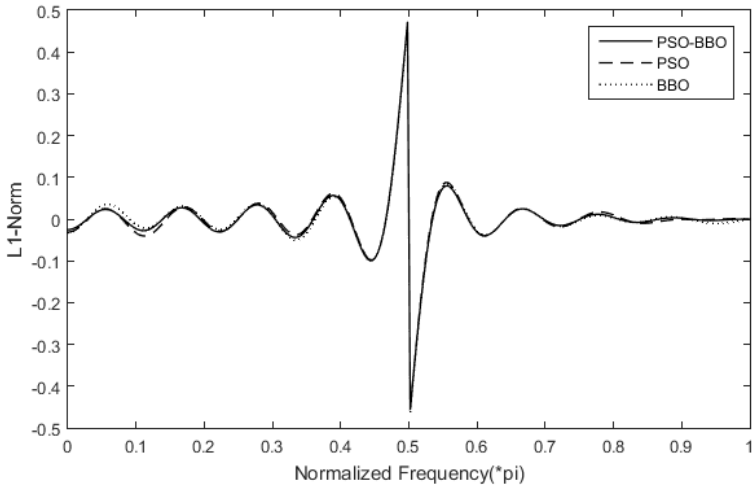

Fig. 5: Ideal filter response

3.4 L2 Error

L2= (Ideal filter response- Practical filter response) ^2

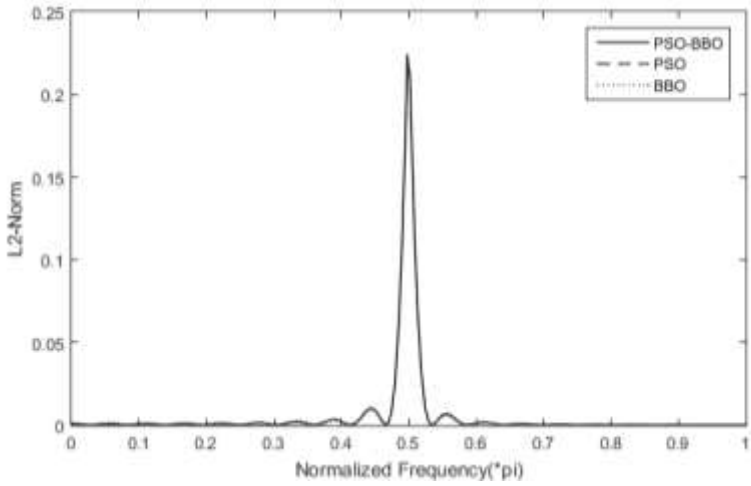

Fig. 6: Ideal filter response

4. CONCLUSION

In this paper, three optimization techniques, i.e., PSO, BBO and BBO_PSO are applied for the designing of N=36 Low Pass FIR filter. In which BBO_PSO outperforms among the optimization techniques in which they showed the better error performance in terms of L1 and L2. Many optimization techniques still pending which may give the better result in future work.

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