Survey on Design of Digital FIR Filters using Optimization Models

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Abstract

As the discipline of Digital Signal Processing develops, digital filters play an increasingly vital role in modern technology (DSP). The FIR filter, which stands for "finite impulse response," is the most common type of filter. As a result of its versatility, FIR filters find widespread application in many fields, including image filtering, frequency modulation, precision arithmetic, and many more. For this reason, digital FIR filters are designed using various optimization techniques. Using various optimization strategies yields the best results when optimizing for different filter coefficients (concerning control parameters, dependence, premature convergence, etc.). They're advantageous due to several factors, including their straightforward implementation, low error function, high-quality searching ability, and rapid convergence. In this paper, we have covered the topic of designing efficient digital filters for signal, image, and video processing using various optimization techniques.

Keywords: Keywork one; Keywork two; Keywork three; Keyword four; ….

1. Introduction

The primary function of digital filters is to either reduce the size of an input signal or to extract specific features from it. The method relies on applying mathematical operations to a numerical representation of a discrete-time signal. Finite impulse response (FIR) and infinite impulse response (IIR) filters are two categories used to categorise digital filters [1]. (IIR). These filters are further divided into one-dimensional (1D) filters and two-dimensional (2D) filters for signal and image processing based on the dimensionality of the input signal. It is usual practise to prefer FIR digital filters over IIR filters due to their inherent stability and the ability to have linear phase. Many crucial tasks in digital signal and picture processing rely on these FIR filters.

Finding the filter coefficients which controls filter performance is a key part of digital filter design. For filter design, the status quo includes numerous tried-and-true approaches, such as the use of windowing functions like Butterworth, Chebyshev, Kaiser, etc., or the application of transformation techniques like the bilinear transformation. While the Remez exchange algorithm described by Parks and McClellan and the Steepest-descent approach for optimising digital filter development via the selection of filter coefficients are both effective, they are not well suited for optimising FIR filters for a number of reasons [2].

Doi: https://doi.org/10.54216/JAIM.020102
Received: April 08, 2022 Accepted: October 19, 2022

When there isn't just one right way to do something, but rather several that could work, an optimization algorithm is a strategy for finding the best possible solution. Part of the process involves determining which criteria are most important, assessing each solution set, and then ranking the alternatives from best to worst. There have been previous attempts at optimal filter design, and the invention of optimised filter coefficients is not new. For the most effective digital filter design, researchers use evolutionary optimization techniques such as the Genetic Algorithm [3], Artificial Bee Colony optimization [4], Differential Evolution [5], and PSO [6]. These methods have been shown to be highly effective [7, 8], since they allow for greater manipulation of performance factors, while also reducing inaccuracy and boosting response quality thanks to the attenuation provided by a wide stop band.

For a FIR filter to function well and reliably in a given setting, it is crucial that the design process be carried out correctly. Several methods have been offered for designing filters that can produce the required frequency response. But there are still obstacles to overcome. To achieve a sharper cut-off and lower filter order while simultaneously minimising ripple content in the pass band and stop band presents a significant challenge for design engineers. Traditional methods for designing FIR filters include the windowing and frequency sampling method. Kaiser and Helms proposed the most popular methods for optimum windowing. Unlike Dolph Chebyshev windowing, which uses inverse hyperbolic cosines to produce window coefficients, Kaiser windowing obtains filter coefficients in windowing by computation of Bessel functions. Other than these, however, windowing approaches do not provide fine-grained control over parameters like pass-band and stop-band cut-off frequencies and transition width.

In recent years, numerous evolutionary optimization strategies have been used extensively in the development of FIR filters. These methods accomplish the aforementioned goal by treating the filter design work as an optimization problem, the solution to which is an iterative process of identifying a set of filter coefficients that satisfies the requirements. To do this, an error function (objective function) is formulated to quantify the gap between the filter's output and the desired output. To successfully construct a filter, it is necessary to choose an appropriate error function and optimization method. While gradient-based optimization approaches are computationally inexpensive, they frequently produce a solution that is not globally optimal, leading to coefficients that do not fully meet the criteria.

Several facets of FIR filter design have benefited from the application of convex optimization techniques [9-11]. Frequency-domain optimal FIR filter design, on the other hand, typically involves a nonconvex optimization problem with several local optimal points due to the nature of the error function. This non-convexity results from the fact that the connection between the filter coefficients and the frequency response is exceedingly intricate and nonlinear. Researchers have looked into using evolutionary optimization techniques for FIR filter design due to its potential for efficiently handling multimodal (many local optima) optimization challenges. The evolutionary methods have a higher chance of convergent to the globally optimal solution than the gradient based methods. In contrast to the often-obtained suboptimal answer for gradient-based approaches, the post-convergence solution provided by evolutionary techniques yields filter coefficients that maximally satisfy the intended frequency response. Similarly to heuristic-based approaches, evolutionary optimization-based approaches produce a solution that is indifferent to the parameters with which it was initially implemented.

2. FIR Filter Design using Optimization

Each optimization method has the same overarching goal: to find the values of the coefficients h, R, and m that will allow the filter to function as required. By repeatedly adjusting the coefficients, the optimization-based design methods bring the filter's frequency response closer to the ideal. Error is expressed as a numerical value using the error function, which connects the answer in terms of the coefficients, as

$$E_c(e^{j\omega}, h) = H_I(e^{j\omega}) - H_D(e^{j\omega}) \tag{1}$$

The Chebyshev error is given as

$$E_{ch} = \min\{\max W(\omega)|\, E_c(e^{j\omega}, h)|\} \tag{2}$$

Doi: https://doi.org/10.54216/JAIM.020102
Received: April 08, 2022 Accepted: October 19, 2022

Where W (ω) is the weighting function. The presence of absolute function in (2) makes it nonlinear in which the coefficients remain inside a circle with radius $\frac{E_{ch}}{w(\omega)}$ cantered at the origin, of the complex plane. Different method uses L_p norms [12]. Chebyshev approximation (p = ∞) is the most used in all different methods, whereas some have quantified the error in least squares [13,14,15] (p = 2), sense. The Chebyshev approximation [16,17,18,19,20] are modified with specified error bounds (ripples) in pass band (δp) and stop band (δs) as

$$E_{chm} = \min\{\max\left|E_c(e^{j\omega},h) - \delta_p\right| + \max\ |E_c(e^{j\omega},h) - \delta_s|\} \tag{3}$$

Similarly, for least square error [21]

$$E_{lsm} = min\sum_{k=1}^{K}|E_c(e^{j\omega},h)|^2 \qquad s.t.\left|E_c(e^{j\omega},h)\right| < (\delta_p,\delta_s) \tag{4}$$

In [22], the complex error is replaced by absolute error

$$E(e^{j\omega},h) = \left|H_I(e^{j\omega})\right| - \left|H_D(e^{j\omega})\right| \tag{5}$$

Logarithmic error has been considered [23] as

$$E_1(e^{j\omega},h) = lnH_I(e^{j\omega}) - \ln H_D(e^{j\omega}) \tag{6}$$

Finding the optimal coefficients, is made more difficult due to the nonlinear relationship between the filter coefficients and the error functions (3-6), which makes the relevant optimization problem non-convex and multi-modal with several local optimal points. The two most popular evolutionary techniques, the genetic algorithm (GA) and the particle swarm optimization (PSO), were used to compare the effectiveness of the error above functions in building a filter to a given set of parameters. Pass-band cut-off frequency is 0.45 GHz, stop-band cut-off frequency is 0.55 GHz, the pass-band ripple (PBR) is 0.01 Hz, and the stop-band wave (SBR) is 0.01 Hz. For a filter of order 20, all error functions are solvable.

Several trial runs are conducted with various GA control parameters before settling on 50 for population size, 0.65 for the cross-over rate, and 0.2 for the mutation rate. There have been 500 iterations of the algorithm. The same values were chosen for PSO's control parameters: 30, 1, 1, 0, 2, and 0.20 for the maximum velocity and learning factor, respectively.

2. Optimization Techniques Evolution for FIR Filter Design

In order to identify the ideal solution, i.e., the filter coefficients, researchers have turned to computationally efficient evolutionary algorithms. As opposed to traditional optimization methods, evolutionary optimization starts with a population of points rather than a single point, and it has less of a chance of being stuck in suboptimal "false minima" (local minima). These algorithms often employ a concurrent, stochastic search method rather than a deterministic one.

These algorithms and their enhanced variants learn from their past mistakes and use that data to converge to the best possible answer as quickly as possible. In terms of their ability to converge on global optimum solutions, evolutionary algorithms excel. Due to these merits, evolutionary methods have found widespread application in FIR filter construction.

In [24], it is shown that the most popular evolutionary method, the genetic algorithm (GA), outperforms the sequential approach. As a result, it provided a straightforward, automated procedure for building FIR filters with almost optimal frequency response and little hardware complexity. In [25], GA is used to construct a multiplier-free FIR filter, outperforming the equiripple (minimax) alternative in terms of both area and speed. In [26], GA is implemented in Farrow-structured fractional-delay FIR filters.

Using least squares and minimax error functions, the evolutionary algorithm has been used to the construction of FIR filters [27]. Minimax method has been found to be more effective than least squares. Logarithmic error-based linear and nonlinear phase FIR filters are constructed with GA in [28]. Combining simulated annealing (SA) and Tabu search (TS) with a genetic algorithm (GA), with coefficients expressed in hardware-compatible format (i.e., signed power of two), is proposed in [29]. (SPoT). The quantization error can be minimised by using this representation.

Doi: https://doi.org/10.54216/JAIM.020102
Received: April 08, 2022 Accepted: October 19, 2022

Power consumption can be lowered by further minimising the need for switching between the coefficients. In [29], a hybrid approach was used to enhance solution quality while simultaneously decreasing computing effort. According to [30], an L1 norm based real-coded genetic algorithm (RCGA) is superior to a more traditional particle swarm optimization (PM) method when it comes to designing optimal band stop filters.

Due to the dependence of gradient-based approaches on initial conditions, an SA-based approach led to better FIR filter design in [31]. The slower convergence and increased number of control parameters are, nevertheless, shared by GA and SA. Differential evolution (DE) algorithms have been applied to FIR filter design in [32,33] with varying orders and specifications to address the drawbacks of GA and SA. Given an identical population size and set of function evaluations, the DE technique provided faster convergence than the GA approach. Hardware efficient FIR filters have been designed using DE and common subexpression elimination (CSE) in [34].

Filter coefficients (in SPoT representation) have been derived using DE, satisfying the required frequency domain parameters; furthermore, CSE has been implemented to lessen the hardware requirements. Space, time, and energy needs have all been reduced substantially. In [35], DE was combined with PSO to provide a new method for designing FIR filters, which outperformed methods based only on PSO. In [37], a hybrid adaptive DE (ADE) and PSO (ADEPSO) is employed, which outperforms PSO, DE, ADE, and DEPSO not only in reaching the desired magnitude response but also in converging faster toward the optimal solution.

Low pass, high pass, band pass, and band stop FIR filters have all been designed using DE and wavelet mutation in [38]. The transition width was compromised in [38] to achieve lower ripples in the pass band and the stop band. In [39], DE is used to create hardware-optimized FIR filters with SPoT coefficients. In order to meet the required parameters, [40] investigates how a mutant factor influences the design of DE-based FIR filters in addition to minimising SPoT terms. FIR filter design using a refined form of DE has been applied to the problem of flaw identification in paper manufacturing [41].

Particle swarm optimization (PSO) is a type of algorithm that may update itself without the use of genetic operations like crossover or mutation, unlike GA and DE. In [36,42], PSO is used to construct FIR filters and is shown to be superior than the GA due to its ease of use, its dynamic behaviour, and its ability to exploit the cooperative behaviour of biological species. As opposed to the previously reported methods, the ripples in the pass band and the stop band are specified independently in [36].

Premature convergence and instability are problems that can affect traditional PSO. There have been attempts to solve the FIR filter design problem using modified versions of PSO [43,44,45]. Craziness-based PSO (CPSO) was found to match the predefined parameters to the greatest extent among the novel PSO (NPSO) and CPSO employed for FIR filter design in [43].

Attractive and repulsive PSO (ARPSO) has been employed for filter construction in [45], where it has been proven to outperform the traditional PSO in terms of stop-band attenuation and to avoid premature convergence to the local optima. Based on the refraction concept, [44] employs an enhanced PSO algorithm to construct FIR filters.

Recent work in evolutionary theory has led to the use of an approach with only one tuning parameter, the artificial bee colony (ABC) algorithm, to FIR filter design [46, 47]. This is done in order to circumvent the issue of parameter selection. It has been determined that when compared to the best evolutionary algorithm currently available, ABC achieves the desired PBR more effectively.

When minimising the probability of a bad result (PBR) is a key goal in a filter design application, an ABC-based filter design approach may be preferable. Sharper filters (short transition width) were designed utilising ABC and the FRM method [48]. Since the filter coefficients are represented using canonic signed digits, the filter developed in [48] is not only sharp but also uses less hardware (CSD).

In [49], a control parameter-free seeker optimization method (SOA) is proposed for FIR filter design to address the issue of tuning the control parameter. Ripples in the stop band are much diminished FIR filters designed with seeker optimization (SBR). Although SOA is a control parameter-free method, it provides superior convergence to a near-optimal solution and greater robustness than competing methods. In contrast to traditional methods of FIR filter design, the recently reported evolutionary techniques of opposition-based orthogonal harmony search algorithm (OHS) [50], Cat swarm optimization (CSO) [51], Bacteria foraging optimization (BFO) [52], and Cuckoo search (CS) [53,54] achieve the desired filter design characteristics with comparable performance.

Doi: https://doi.org/10.54216/JAIM.020102
Received: April 08, 2022 Accepted: October 19, 2022

A lowpass filter with the following frequency domain parameters was designed using evolutionary optimization: pass-band frequency=0.45, stop-band frequency=0.55, pass-band ratio (PBR)=0.1, stop-band ratio (SBR)=0.01, and filter order (FIR)=20. Every algorithm underwent the same number of function evaluations on the same computing platform. Table 1 compares the filter parameters reached after convergence using various techniques.

Table 1: Comparison of different optimization algorithms

Method	Optimizer	Passband frequency	Stopband frequency
[46]	hybrid artificial bee colony	0.105	0.03324
[52]	Ghoshal, Bacteria foraging	0.129	0.02773
[35]	Differential evolution particle swarm optimization	0.257	0.02590
[12]	Cuckoo search algorithm	0.064	0.07370
[6]	Particle swarm	0.1230	0.03970
[49]	Seeker	0.138	0.02430

It is clear from Table 1 that the ABC algorithm achieves the PBR at a higher rate than any of the other evolutionary methods. In contrast, OHS achieves the best SBR results of any method we tested. According to Table 1, ABC outperforms other cutting-edge evolutionary optimization methods in terms of PBR and TW. Pass-band and stop-band ripple minimization has been the primary focus of the evolutionary optimization-based strategies we've explored so far. Their efficacy has been confirmed through a comparison of the responses of filters obtained post-convergence to those obtained using alternative evolutionary and classical methods.

Minimizing hardware complexity is a concern that has been tackled in several of these works by using alternate representations for the coefficients (SPoT and CSD). By contrasting the problems solved by classical and evolutionary optimization-based methods, it becomes apparent that documented evolutionary optimization methods have not focused on application-specific design constraints, such as filters with complex coefficients or sparse coefficients.

For linear phase FIR filter applications where long delays are tolerable, complex coefficient filters are the preferable choice [55]. However, this problem has not been addressed by evolutionary optimization-based FIR filter design methods. Filter design that takes into account implementation concerns such power consumption, filter execution, quantization error, and hardware demand can result in significant improvements in these areas. While the filter designer has no say on the underlying implementation architecture, he or she can influence how many multipliers are needed by limiting the number of filter coefficients that are not zero. In this context, classical filter design methods have been used to the creation of sparsity-controlled FIR filters [56, 57, 58].

The design of sparse FIR filters has not been studied by methods based on evolutionary optimization. Convergence speed, defined as the amount of time it takes to reach a stated criterion, is an important feature of any evolutionary optimization technique in addition to convergence to the global solution. The computational cost of the described methods was compared by measuring how long each one took to run on a standard platform and reach a predefined convergence criteria. A low pass filter with pass-band and stop-band frequencies of 0.30 and 0.50 Hz, respectively, has been optimised using the objective function limited Chebyshev with absolute error function. Figure 1 depicts the amount of time needed to carry out various algorithms.

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Algorithm	Stopping criterion				
	3	2	1	0.5	0.25
PSO					
Min	0.0800	0.0989	11.0351	19.0133	46.3420
Max	2.1337	5.1453	15.1459	33.6556	50.9249
Mean	1.9903	5.1021	13.1154	25.4990	46.6724
SD	0.0119	0.146	1.1071	2.2612	4.2164
SOA					
Min	0.8664	1.7811	12.3066	24.1301	35.5738
Max	2.9807	5.3867	14.2521	28.7452	48.6941
Mean	1.5150	4.9430	13.9825	26.2180	42.7501
SD	0.7515	0.879	1.3444	2.9525	3.6619
CSO					
Min	0.9474	1.0223	18.5379	20.5500	39.1223
Max	1.8913	5.4477	19.3771	29.6938	51.2235
Mean	1.7979	4.4863	17.2842	28.4756	49.9909
SD	0.2592	0.8110	1.0231	2.6038	2.3157
GA					
Min	1.5212	2.2464	8.4351	15.8653	50.0101
Max	3.3979	6.4577	12.8795	23.4323	23.4021
Mean	3.2739	5.4365	10.7346	22.0634	51.2798
SD	0.944	1.5250	1.9541	2.3891	5.1032
ABC					
Min	0.3087	3.6325	6.0441	12.4025	36.4300
Max	4.6554	6.6025	7.6025	28.8261	44.4048
Mean	2.5255	4.0502	7.0502	20.4168	40.6868
SD	0.6244	0.8446	1.5436	4.3206	5.7960

Figure 1: Comparison between different algorithms execution time.

Figure 1 shows that SOA and ABC perform better than alternative evolutionary algorithms towards the beginning and end of the error function's range. Most methods for designing FIR filters using evolutionary optimization have a single, overarching goal in mind, such as reducing power consumption, jitter, or phase noise. Furthermore, when a FIR filter is developed with a certain goal in mind, it fails to deliver in other areas. Filters with low PBR are essential in high-fidelity audio systems, Hilbert transformers, and communications networks. However, increased stop-band attenuation (small SBR) is necessary in applications like noise removal from biological signals.

It is not possible to simultaneously minimise the PBR and SBR value for lower order FIR filters. Power is used more by filters that have been designed for frequency domain characteristics (PBR and SBR) and vice versa [59]. Lagrange's multiplier, which provides distinct weightages to the many objectives, can be used to solve the challenge of satisfying competing objectives [60]. However, for given established parameters, the selection of correct weightage function to solve the problem is not known a priori and is selected based on trial and error, making the selection of weight factor a critical problem in these procedures.

Multi-objective optimization, which takes into consideration the trade-offs between conflicting goals, can help find a solution to the problem. [61] describes one approach to the problem of FIR filter design based on multi-objective optimization. Specifically, the research presented in [61] tackles the tension between three competing goals: low power consumption, little ripple in the pass band, and a narrow stop band. The filter order and the amount of ripples produced also have an inverse relationship. As the order of the filter is raised, the frequency response becomes smoother and less prone to ripples [62,63].

Doi: https://doi.org/10.54216/JAIM.020102
Received: April 08, 2022 Accepted: October 19, 2022

3. Methods for Using Optimised FIR Filters

Besides the studies mentioned previously, some other application-specific efforts on evolutionary optimization-based FIR filter design have been described in [64,65,66,67,68,69,70,71-73,74,75,76]. Based on their intended use, these works can be divided into two categories: communication systems and biological signal processing. While FIR filters are typically employed to remove noise from biological signals, they are used for signal separation in communication systems.

FIR filters are commonly utilised in communication systems [77,66,71,74], particularly in the modulation [66] and IF stage of the reception [71]. This is because of the need for linear phase and stability in these applications. Experimental verification of the effectiveness of the DE optimised filters utilised for the pulse shaping filter in the QPSK modulated system has been shown through the use of eye diagrams in [66]. When it comes to subband coding and data transmission, FIR filters based on evolutionary optimization have been applied in [74]. Subband coding is a useful tool, and it has been shown in [74] that FIR filters based on evolutionary optimization perform better than those based on traditional (quasi-Newton and Nelder Mead) approaches.

Therefore, FIR filters are favoured over their IIR counterparts in biomedical applications because of their greater ability to maintain a highly linear phase, which is necessary to eliminate unwanted distortions in the detected signals [76]. Denoising electrocardiogram (ECG) signals and medical imaging are two examples of where one- and two-dimensional FIR filters have been put to the experimental test. The filter developed by the FGA is compared to industry standards. Noise-filled electrocardiogram (ECG) data and pictures have been used to evaluate the performance of the developed filters [76].

It is possible to clean up a signal by employing a FIR filter, which filters out frequencies outside of the signal's intended range. As seen in [70], the craziness-based PSO (CRPSO) has been used for audio processing and the efficient design of FIR filters. In comparison to other methods, the CRPSO-based method has better PBR and SBR values, a sharper cut-off, and a higher signal-to-noise ratio.

For the purpose of cleaning up electroencephalogram (EEG) and event-related potential (ERP) signals, [64] presents an ABC-based adaptive noise canceler based on a finite-impulse-response (FIR) filter. When compared to gradient-based techniques like LMS [67] and RLS, ABC performs better in a noisy environment, as measured by signal-to-noise ratio (SNR) and the correlation between ERP and mean value difference.

However, in modern hearing aids, FIR filters are used because their linear phase property aids in distinguishing between music sources of varying frequencies, which the human ear is insensitive to [72]. Using a combination of genetic algorithm (GA) and differential evolution (DE)-based optimization, the authors of [32] created a hearing aid with little complexity by implementing sub and Farrow based filters. It has been determined that the proposed algorithm can lower both the number of adders and the amount of time required by the CPU [77-79].

4. Conclusions

This study provides a summary of the methods that utilise evolutionary optimization in FIR filter design. When viewed as an optimization problem, filter design is first reduced to the process of minimising an error function that represents the filter's features. In this study, we categorised the reported error functions as either complex, absolute, or logarithmic. An analysis utilising a popular evolutionary method, GA, has been undertaken to evaluate the efficiency of the error functions. In this study, we classify the optimization-based FIR filter design methods into traditional and evolutionary paradigms. Specifications, computational time, hardware compatibility, applications in communication systems and biomedical signal processing, etc., related to the proposed evolutionary optimization approaches have been examined. Similar to error functions, the reported evolutionary techniques have been quantitatively analyzed and compared in terms of meeting the desired specifications.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

Doi: https://doi.org/10.54216/JAIM.020102
Received: April 08, 2022 Accepted: October 19, 2022

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