

# Design of FIR Filter Using Differential Evolution Optimization & to Study its Effect as a Pulse-Shaping Filter in a QPSK Modulated System

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## Summary

In order to reduce the effect of Inter Symbol Interference (ISI) in a digital communication system, different types of transmitting pulse shaping filter has been extensively used in practice. We need to design these filters with some constraints imposed by requirements of the communication system in which we are going to use them. The use of different optimization technique, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), has been proved to be quite useful towards the design of those digital filters with certain specifications. In this paper, we have proposed a linear phase FIR digital filter, which has been designed using Differential Evolution (DE) algorithm. The performance of the proposed filter has been examined by recording the variation of the resulting frequency response with number of iteration and population size. The convergence behavior of the optimization technique has also been studied. In addition, the proposed FIR filter has been used as a pulse-shaping filter in a Quadrature Phase Shift Keying (QPSK) modulated system and its performance has been evaluated in terms of some system parameters like Error Vector Magnitude (EVM), Signal to Noise Ratio (SNR) and Waveform Quality Factor ( $\rho$ ). The Eye diagram of the system has also been presented for the proposed filter along with the standard filters like, Raised Cosine (RC) and Root Raised Cosine (RRC) to study the impact of these filters on system ISI.

## Key words:

DE, FIR digital filter, Minimax error, QPSK.

## 1. Introduction

Digital filter contains adder, multiplier and flip-flops. The amplitude by which each sample of the input to the filter is multiplied is nothing but the coefficients of the impulse response. Depending upon the impulse response of any digital filter, its characteristics will vary. In order to implement low-pass, high-pass or band-pass digital filter, the impulse response of each of them is different from others. It is always possible to design an FIR filter transfer function with an exact linear-phase response, while it is nearly impossible to design a linear-phase IIR filter transfer function [1]-[3]. That is why in many practical system, FIR digital filter is normally used. In any digital

communication system, transmitting pulse-shaping filters are generally realized by different types of FIR filter.

An FIR digital filter design technique using PSO has been illustrated in [4]. In this paper, two design cases, namely low-pass and band-pass FIR digital filter have been presented. Moreover, the utility of various error norms such as Least Mean Squares (LMS) and Minimax, and their impact on the convergence behavior and optimal resultant frequency response have been examined. The effect of different population size and iterations in PSO based FIR filter design has also been investigated.

An application of PSO in the design of stable IIR digital filters with non-standard amplitude characteristic has been presented in [5]. It has been shown that the design of IIR digital filters with non-standard amplitude characteristics, which considerably differ from typical Butterworth, Chebyshev, and Cauer approximations, is possible using PSO. The IIR digital filter designed in this way is stable and fulfills all prescribed design specifications.

The design of two-dimensional IIR digital filters using an improved Quantum-behaved Particle Swarm Optimization (QPSO) algorithm has been presented in [6]. In this paper, improved QPSO, called Diversity-Guided QPSO (DGQPSO) has been proposed to obtain the solution of the design problem. The DGQPSO has been implemented by controlling the diversity measure of the swarm to enhance the global search ability of the QPSO. It has also been established that the results obtained by DGQPSO is superior to other competitive optimization algorithms.

The design of robust stable digital filter by DE algorithm has been described in [7]. A robust stability criterion, which would be used to ensure the stability of the digital filter in the evolution of DE, has been derived. It has been observed that the performance of DE is superior to that of GA in the filter design problem.

An efficient pulse-shaping filter architecture for single sideband/binary phase shift keying-double sideband/code

division multiple access (SSB/BPSK-DS/CDMA) has been presented in [8]. The proposed architecture is based on linear-phase property and the look-up table method. By synopsis simulations, it has been shown that use of the proposed method can result in a reduction in the number of gates by 40%.

In this paper, we have designed a pulse-shaping low pass FIR digital filter using DE algorithm. The frequency response of the designed FIR filter for different population size and iterations has been presented. We have also compared the variation of averaged cost function of the design algorithm with population size and the number of iterations. Minimax error norm has been considered as averaged cost function in our algorithm. The proposed FIR digital filter has been used as a pulse-shaping filter in a QPSK modulated system to study its impact on the system performance.

## 2. Differential Evolution

In the year 1995, Price and Storn have proposed a new floating-point encoded evolutionary algorithm for global optimization. The name of the algorithm is Differential Evolution (DE) algorithm to signify a special type of differential operator that has been utilized to create new off springs from the parent chromosomes without adopting classical crossover or mutation. It is a new heuristic algorithm for minimizing possibly nonlinear and non-differentiable continuous space functions. By means of an extensive test bed it has been demonstrated that this method converges faster and with more certainty than any other global acclaimed optimization technique [9]. This algorithm can be implemented very easily and it requires negligible parameter tuning, which has made the algorithm reasonably popular very soon [10]-[11].

DE is a very simple, powerful, stochastic, population-based, robust, easy to use optimization algorithm, which has been developed to optimize real parameter and real valued functions. DE evolves different generations until the stopping criterion is reached. General problem formulation for DE is for an objective function  $f: X \subseteq \mathbb{R}^D \rightarrow \mathbb{R}$ , the goal of the optimization technique is to find  $x^* \in X$  such that  $f(x^*) \leq f(x)$  for all  $x \in X$  [12]. The crucial idea behind DE is a new scheme for generating trial parameter vectors. DE generates new parameter vectors by adding the weighted difference vector between two population members to a third member. If the resulting vector yields a smaller objective function value than a predetermined population member, the newly generated vector replaces the vector with which it was compared. The comparison vector can, but need not be the part of the generation process. In addition, the best

parameter vector is evaluated for every generation in order to keep track of the progress that is made during the minimization process [9]. There are different variants of DE scheme, which are now being used in practice. Mutation is that particular step in DE, which is responsible for different types of DE technique. It is a very good global optimizer for function optimization [9]-[13]. It has found its applications in design of digital filters [12], electromagnetic inverse problems [13]-[14], composite materials [15], antennas [16] and different other mathematical and engineering domains.

This algorithm can optimize any function with D real parameters for any positive integer number D. Before the start of the algorithm, the size of the population P should also be selected. P does not change during the minimization process. So, DE will utilize P number of D dimensional vector with each vector having the form:

$x_{i,G} = [x_{1,i,G}; x_{2,i,G}; \dots; x_{D,i,G}]$ , where  $i=1,2,\dots,P$  and G is the iteration number or generation number.

This evolutionary algorithm includes four steps, namely Initialization, Mutation, Recombination and Selection.

### 2.1 Initialization

This step indicates the start of the evolutionary algorithm. Initially, the values associated with the parameter vector are chosen randomly and it should cover the entire parameter space. Unless otherwise mentioned, generally a uniform probability distribution for all the random variables is assumed. In case of a preliminary solution is available, the initial population is often generated by adding normally distributed random deviations to the nominal solutions [17]. Let  $x_{i,j,1}$  denote the  $i^{\text{th}}$  element of the  $j^{\text{th}}$  member of population at first iteration. In order to ensure that this value is within a certain limit  $[x^L, x^U]$ ,  $x_{i,j,1}$  is chosen according to the following equation:

$$x^L \leq x_{i,j,1} \leq x^U \quad (1)$$

where  $x^L$  and  $x^U$  are the upper and lower bound of the random variable respectively.

### 2.2 Mutation

The step mutation actually expands the search space [12]. In each generation or iteration of the algorithm, to change the member of the population  $x_{i,G}$ , a mutant or donor vector  $V_{i,G+1}$  is created. Depending upon the generation of the donor vectors from the parameter (target) vector, different variants of DE has been developed [10]. For each parameter vector  $x_{i,G}$ ,  $i=1, 2, \dots, P$ ; a mutant vector is generated using different equations in different schemes of DE. In the DE/rand/1 scheme, mutant vector of the next

generation  $v_{i,G+1}$  is generated according to the following equation [9]-[10]:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \quad i = 1, 2, \dots, P \quad (2)$$

where  $i$ ,  $r1$ ,  $r2$  and  $r3$  are distinct from each other and chosen from the set  $\{1, 2, \dots, P\}$ .  $F$  is the weighting factor which is in the range  $[0, 2]$  and it will control the variation of the amplification of the differential variation  $(x_{r2,G} - x_{r3,G})$ . In order to ensure that the running index  $i$  is different from the other three distinct indices  $r1$ ,  $r2$  and  $r3$ ; the minimum number of population in this particular scheme of Differential Evolution technique must be 4.

DE/rand to best /1 follows the same procedure as that of DE/rand/1. The only difference is that the donor vector  $v_{i,G+1}$  is created using any two randomly selected parameter vector and the best member of the current generation. This can be represented mathematically [10], in accordance to the following equation:

$$v_{i,G+1} = x_{i,G} + \lambda(x_{best,G} - x_{i,G}) + F(x_{r2,G} - x_{r3,G}) \quad (3)$$

where  $\lambda$  is a control parameter from the set  $[0, 2]$ .

In the scheme DE/best/1 and DE/best/2, mutant vector of any generation is produced without using the corresponding parameter vector. The donor vectors for each of these two schemes are given by (4) and (5) respectively [10]:

$$v_{i,G+1} = x_{best,G} + F(x_{r1,G} - x_{r2,G}) \quad (4)$$

$$v_{i,G+1} = x_{best,G} + F(x_{r1,G} + x_{r2,G} - x_{r3,G} - x_{r4,G}) \quad (5)$$

Another different DE scheme is known as DE/rand/2. Here, in order to construct a donor vector, altogether 5 distinct parameter vectors are randomly chosen from the rest of the population. In this process, two weighted difference vectors are added to the same to generate the donor vector [10], as shown in (6):

$$v_{i,G+1} = x_{r1,G} + F_1(x_{r2,G} - x_{r3,G}) + F_2(x_{r4,G} - x_{r5,G}) \quad (6)$$

where  $F_1$  and  $F_2$  are two weighing factors selected in the range from 0 to 1.

### 2.3 Recombination

Recombination incorporates successful solutions from the previous generation [12]. In order to increase the potential diversity of the population member, Recombination process plays a very important role. At the end of this step, the trial vector  $u_{i,G+1}$  is developed from the elements of the target vector  $x_{i,G}$  and the elements of the donor vector  $v_{i,G+1}$ . Elements of the donor vector enter the trial vector with probability  $RP$ . The trial vector has the form:

$$u_{i,G+1} = [u_{1,i,G+1}; u_{2,i,G+1}; \dots; u_{D,i,G+1}] \quad (7)$$

where  $i = 1, 2, \dots, P$ .

Each member of the trial vector is formed in accordance to the following equation [12]:

$$u_{j,i,G+1} = \begin{cases} v_{j,i,G+1} \Leftrightarrow \text{rand}_{j,i} \leq RP \vee j = I_{rand} \\ x_{j,i,G} \Leftrightarrow \text{rand}_{j,i} > RP \wedge j \neq I_{rand} \end{cases} \quad (8)$$

where  $\text{rand}_{j,i}$  is a random fractional value in the range  $[0, 1]$  and  $I_{rand}$  is a random integer from  $[1, 2, \dots, D]$ .  $RP$  denotes the recombination probability and certainly is in the range  $[0, 1]$ .  $I_{rand}$  ensures that  $u_{i,G+1} \neq x_{i,G}$ . In other words, we can say that  $u_{i,G+1}$  gets at least one parameter from  $v_{i,G+1}$  for  $i$  to be in the range  $[1, 2, \dots, P]$ .

### 2.4 Selection

This is the final step of the evolutionary algorithm. To decide whether or not the trial vector  $u_{i,G}$  has become able to be a member of the next generation  $G+1$ , it is compared to the target vector  $x_{i,G}$  and that particular vector which yields lower functional value than the other is allowed to enter into the next generation. This can be represented mathematically as follows [12]:

$$x_{i,G+1} = \begin{cases} u_{i,G+1} \Leftrightarrow f(u_{i,G+1}) \leq f(x_{i,G}) \\ x_{i,G} \Leftrightarrow f(u_{i,G+1}) > f(x_{i,G}) \end{cases} \quad (9)$$

If the trial vector  $u_{i,G+1}$  yields smaller cost function than the target vector  $x_{i,G}$ , then the value of  $u_{i,G+1}$  is assigned to  $x_{i,G+1}$ . Otherwise, the old value of the target vector  $x_{i,G}$  will be sustained.

Mutation, Recombination and selection process will continue until any stopping criterion is arrived. If after the execution of all the iterations, stopping criterion is never achieved then the member of the population having the least functional value is chosen as the optimized solution to the problem of concern.

## 3. Problem Formulation

The transfer function of a causal FIR filter of length  $L+1$  is given by [1]:

$$H(z) = \sum_{n=0}^L h[n]z^{-n} \quad (10)$$

In case of causal transfer function, the phase distortion can be avoided by ensuring a linear-phase characteristic in the frequency band of interest. The linear-phase relationship can be guaranteed if the impulse response is either symmetric i.e.

$$h[n] = h[L - n], \quad 0 \leq n \leq L, \quad (11)$$

or is anti-symmetric [1], i.e.

$$h[n] = -h[L - n], \quad 0 \leq n \leq L, \quad (12)$$

We have used the symmetric property of impulse response in our design. Our design problem requires the values of  $[\frac{L+1}{2}]$  number of coefficients in order to obtain the digital low pass filter with certain characteristic. The frequency response of the digital filter, with impulse response  $h[n]$ , is given by [1]-[3]:

$$H(e^{j\omega}) = \sum_{n=0}^L h[n]e^{-j\omega n} \quad (13)$$

Let the transfer function of the ideal low pass digital filter is given by  $H_{ideal}(e^{j\omega})$ . Our objective in the digital filter design by Differential Evolution technique is to find out the values of  $h[n]$  in such a way that the resulting filter transfer function  $H(e^{j\omega})$  closely approximates that of the ideal one, i.e.  $H_{ideal}(e^{j\omega})$ . We have sampled both  $H(e^{j\omega})$  and  $H_{ideal}(e^{j\omega})$  into equal frequency intervals and obtained the corresponding error values. Minimization of these error values is of primary concern towards the design of low-pass FIR digital filter by DE. The equally spaced sample values of  $H(e^{j\omega})$  and  $H_{ideal}(e^{j\omega})$  are given by  $H(k)$  and  $H_{ideal}(k)$ , defined by:

$$H(k) = |H(e^{j\omega})|_{\omega = \frac{k\pi}{N}}, k = 1, 2, \dots, N \quad (14)$$

$$H_{ideal}(k) = |H_{ideal}(e^{j\omega})|_{\omega = \frac{k\pi}{N}}, k = 1, 2, \dots, N \quad (15)$$

The sampled error function is given by the difference between the frequency sampled values of the ideal frequency response and that of the obtained frequency response.  $E(k)$  denotes the error function, which is defined by:

$$E(k) = H_{ideal}(k) - H(k), k = 1, 2, \dots, N \quad (16)$$

We have run our algorithm for various population sizes and for a number of iterations. In our algorithm, we have used minimax error as the cost function. As the name suggests, this error is defined as minimum of the maximum value of the sampled error function  $E(k)$  which is represented mathematically as follows:

$$\text{Minimax Error} = \min\{Error(i)\}, i = 1, 2, \dots, P \quad (17)$$

$$Error = \max\{E(k)\}, k = 1, 2, \dots, N \quad (18)$$

Using (14), (15) and (16), we can rewrite the above equation as:

$$Error = \max\left\{\sum_{i=1}^N |H_{ideal}(e^{j\omega_i})| - |H(e^{j\omega_i})|\right\} \quad (19)$$

where  $P$  is the number of populations and  $N$  is the total number of frequency samples. If at any particular iteration, the minimax error is less than a specified value then the algorithm terminates and the member of the population with this minimum error is chosen as the solution to our problem. Otherwise, at the end of all the iterations, the member of the population having least Error value will

provide the coefficient of the impulse response of the digital filter.

#### 4. Modulation Accuracy: EVM, SNR and Waveform Quality Factor ( $\rho$ )

In a digital communication system, the transmitter's performance accuracy can be measured in terms of several parameters like, EVM, SNR and Waveform Quality Factor ( $\rho$ ). EVM is defined as the square root of the mean square of the difference between the ideal and actual transmitted signal divided by the mean square of the actual signal [18]. The low value of EVM signifies more modulation accuracy. SNR of a transmitting system is a measure of the system performance and is defined as the ratio of signal power to noise power. A high value of SNR leads to better system performance. The Waveform Quality Factor ( $\rho$ ) is also a measure of the accuracy of the distorted modulated waveform at RF compared to the ideal waveform at digital base band or IF. So  $\rho$  is a correlation measure between the actual waveform and the ideal waveform [18]. A high value of  $\rho$  provides higher accuracy of modulation and hence improved system behavior.

#### 5. Simulation results and its analysis

We have proposed a FIR pulse-shaping filter for QPSK modulated system using DE optimization technique. The design problem has been simulated using MATLAB. The proposed FIR filter has been used as a pulse-shaping filter in a QPSK modulated system and its performance has been studied using Agilent E4438C 250 KHz–3 GHz ESG vector signal Generator (VSG), Agilent E4405B 9 KHz–13.2 GHz ESA-E Series Spectrum Analyzer together with Agilent 89600 Vector Signal Analyzer (VSA) version 5.30 software.

During simulation process, different design parameters have been assigned in the following ways:

DE scheme: DE/rand/1

Weighing Factor: 0.5

No. of trial runs for each population and iteration: 40

Filter length: 8

Filter cut-off frequency: 0.5 rad/pi

The range of each coefficient: [-1, 1]

With the above specifications the generated tap coefficients of the optimized proposed FIR filter have been presented in Table 1 for different population size and iteration number. The filter tap coefficients for standard RRC and RC FIR filters present in VSG have also been included in this table.

Table 1: Tap coefficients of standard and proposed FIR filters

Tap No.	RRC FIR filter taps	RC FIR filter taps	DE optimized FIR filter taps for different population size (P) and different iteration no. (I)		
			P=40 I=80	P=80 I=80	P=100 I=100
0	0.004490	0.015609	0.0037	0.0187	0.0307
1	0.143258	0.174413	-0.1356	-0.1274	-0.0646
2	0.560131	0.588622	0.0777	0.0801	0.0377
3	1.000000	1.000000	0.7270	0.8587	0.7646
4	1.000000	1.000000	0.7270	0.8587	0.7646
5	0.560131	0.588622	0.0777	0.0801	0.0377
6	0.143258	0.174413	-0.1356	-0.1274	-0.0646
7	0.004490	0.015609	0.0037	0.0187	0.0307

The generated coefficients have been interpolated in MATLAB to obtain the impulse response of the proposed FIR filter as presented in Fig. 1.

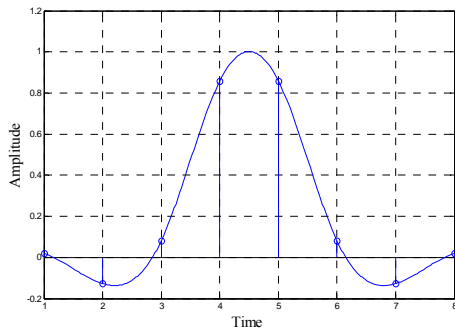


Fig. 1: Impulse Response of proposed low-pass FIR filter (Population size: 80, No. of iterations: 80)

The comparison of magnitude response of the proposed FIR filter for different population size (40, 80, and 100) with a fixed iteration number (80) has been demonstrated in Fig.2. Similar comparison has been presented in Fig.3 and Fig.4 for iteration number 100 and 500 respectively.

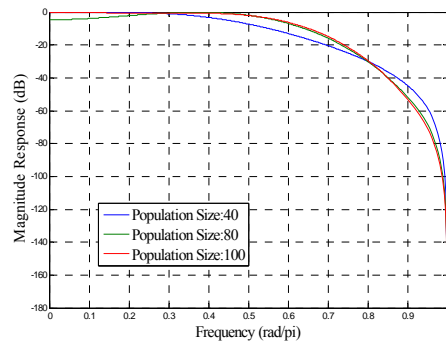


Fig. 2: Magnitude Response of low-pass FIR filter (No. of iterations: 80)

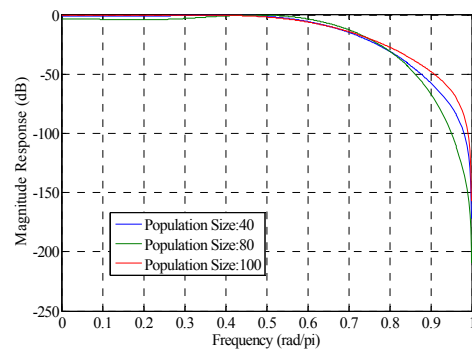


Fig. 3: Magnitude Response of low-pass FIR filter (No. of iterations: 100)

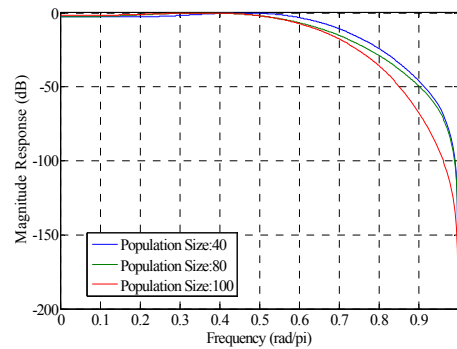


Fig. 4: Magnitude Response of low-pass FIR filter (No. of iterations: 500)

Fig.2 through Fig.4 show that in the pass band the proposed FIR filter behaves ideally for population size 100 with any iteration number. As population size decreases, the behavior of the filter deviates slightly from the ideal one. On the other hand, the performance of the filter improves in the stop band with the increase of iteration number. So the detailed analysis of the above figures indicates that the filter with population size 100 and iteration number 500 exhibits the best performance.

Convergence behavior of DE using minimax error norm in the design of low-pass pulse-shaping transmitting filter has been shown in Fig.5.

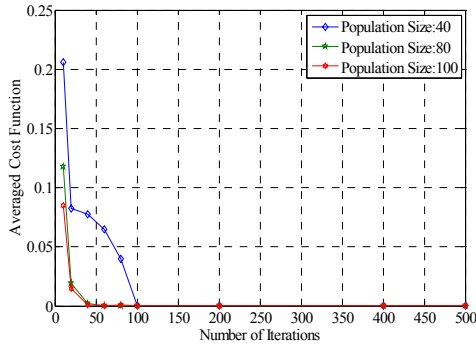


Fig. 5: Convergence behavior of DE in design of low-pass FIR filter  
 In Fig. 5, specifically the convergence behavior for three different population sizes, namely 40, 80 and 100 has been demonstrated. Fig.4 depicts that the averaged cost function curves with population size 80 and 100 attain a very low value with nearly 40 iterations. Where as, to achieve this value the averaged cost function curve with population size 40 needs nearly 100 iterations. Hence the convergence speed becomes faster with increased number of population size.

To analyze the performance of the QPSK modulated system using the proposed FIR filter as pulse-shaping filter, different measurements have been carried out using VSG, spectrum analyzer and VSA software.

The VSG has been characterized in the following ways to generate QPSK modulated signal:

- Baseband data: pn-sequence of length 63
- Symbol rate: 25 Ksps
- Pulse-shaping filter: Nyquist/Root Nyquist/ Proposed FIR filter
- Filter  $\alpha$ : 0.22/0.22/nil
- Modulation type: QPSK
- Carrier frequency: 10 MHz
- Carrier amplitude: 0 dBm

For vector signal characterization, the following options have been used in VSA software:

- Reference filter: Raised-Cosine/Raised-Cosine/user defined
- Measurement filter: off/Root Raised-Cosine/off
- Filter  $\alpha$ : 0.22/0.22/nil
- Symbol rate: 25 KHz
- Modulation format: QPSK
- Result length: 256 symbols
- Points/symbol: 5

The effect of the proposed FIR filter on system Inter Symbol Interference (ISI) has been studied by using Eye diagram of the system. Fig.6 through Fig.9 describe the Eye diagrams for RC and RRC pulse-shaping filters with filter  $\alpha=0.22$  and  $0.35$  respectively. The generated Eye diagrams using the proposed FIR filter with different population size and iteration number have been presented in Fig.10 through Fig.12 for comparison.

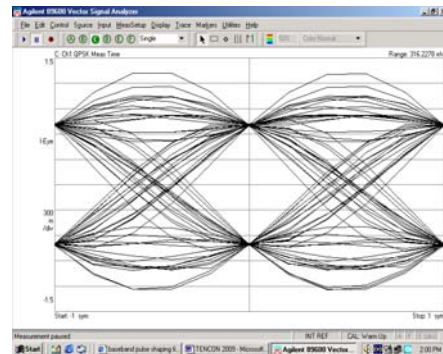


Fig. 6: Eye diagram using RC filter ( $\alpha=0.22$ )

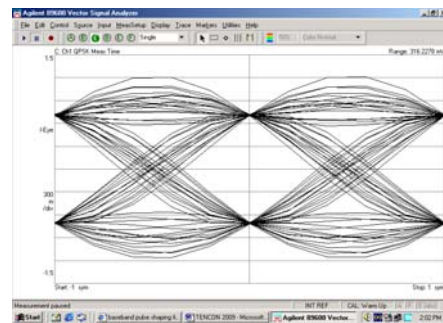


Fig. 7: Eye diagram using RC filter ( $\alpha=0.35$ )

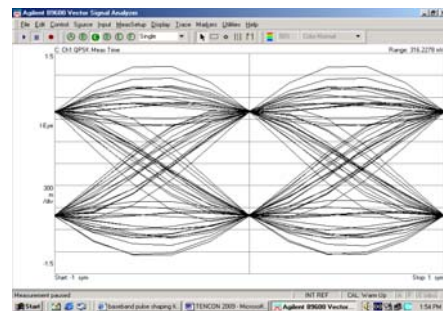


Fig. 8: Eye diagram using RRC filter ( $\alpha=0.22$ )

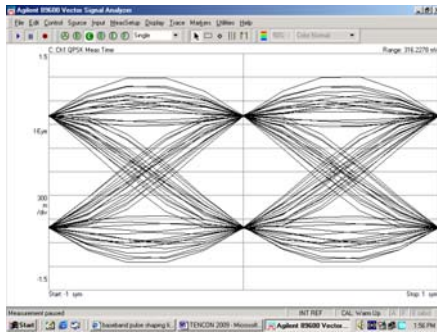


Fig. 9: Eye diagram using RRC filter ( $\alpha=0.35$ )

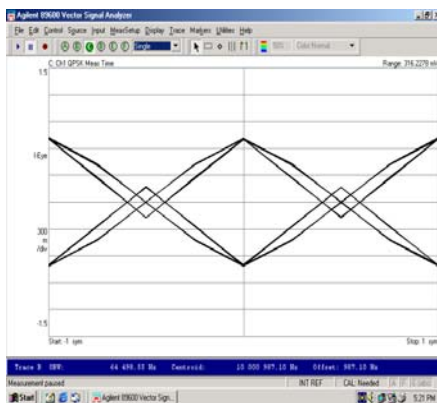


Fig.10: Eye diagram using proposed FIR filter (P=40, I=80)

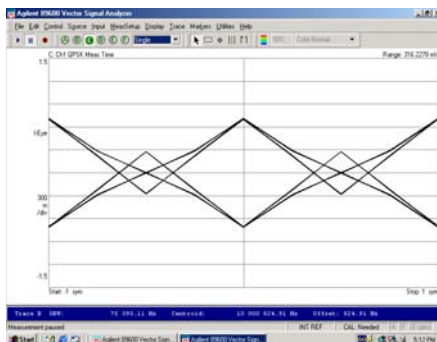


Fig.11: Eye diagram using proposed FIR filter (P=80, I=80)

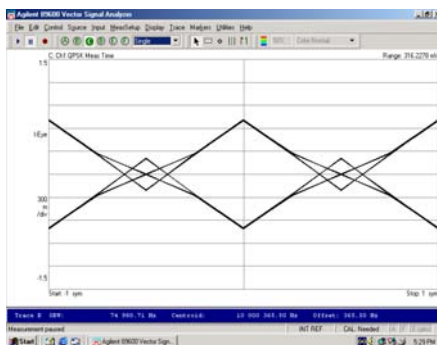


Fig.12: Eye diagram using proposed FIR filter (P=100, I=100)

Comparison of the above figures shows that the Eye width for the proposed filter is more than that of RC and RRC filter. Since the open part of the Eye represents the time over which the signal can be sampled with fidelity, larger the Eye opening, better the result. It is also prominent that the width of crossover in case of proposed filter is less than that of RC and RRC filter. Since the width of crossover represents the amount of jitter present in the signal, small is obviously better. Hence from system ISI point of view the proposed FIR filter performs better.

The performance analysis of a QPSK system using standard RC and RRC filter along with the proposed FIR filter has been summarized in Table 2. The performance of the QPSK modulated system has been evaluated in terms of three parameters namely EVM, SNR and Waveform Quality Factor ( $\rho$ ).

Table 2: Performance analysis of a QPSK system using standard and proposed FIR filter

Type of filter	EVM (%rms)	SNR (dB)	Waveform Quality Factor ( $\rho$ )
RRC ( $\alpha=0.22$ )	0.84	42.2	0.99990
RRC ( $\alpha=0.35$ )	0.67	43.7	0.99994
RC ( $\alpha=0.22$ )	0.91	40.58	0.99992
RC ( $\alpha=0.35$ )	0.90	41.19	0.99991
DE optimized FIR filter (P=40, N=80)	0.653	43.28	0.99995
DE optimized FIR filter (P=80, N=80)	0.640	43.58	0.99996
DE optimized FIR filter (P=100, N=100)	0.635	43.72	0.99997

Table 2 depicts that our proposed filter provides lower value of EVM and higher value SNR and Waveform Quality Factor ( $\rho$ ) compared to those of standard RC and RRC pulse shaping filters. So the DE-optimized proposed FIR filter performs better than the other standard pulse-shaping filters in a QPSK modulated system.

## 6. Conclusions

In this paper, we have designed an FIR digital filter using DE technique and used our proposed DE-optimized filter as a pulse-shaping filter in a QPSK modulated system. The performance of the proposed filter has been analyzed qualitatively and quantitatively along with standard RC and RRC pulse shaping filter. Our proposed filter exhibits better performance as compared to the standard filters with a faster convergence speed. It has also been verified that the FIR filter designed with highest population size and iteration number exhibits the best performance as expected theoretically.

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## References

- [1] S.K.Mitra, Digital Signal Processing: A Computer-based Approach, McGraw-Hill, 2001.
- [2] A. Antoniou, Digital Filters: Analysis, Design and Applications, McGraw-Hill, 2001.
- [3] B. Somanathan Nair, Digital Signal Processing: Theory, Analysis and Digital-filter Design, Prentice-Hall, 2004.
- [4] M. Najjarzadeh and A. Ayatollahi, "FIR Digital Filters Design: Particle Swarm Optimization Utilizing LMS and Minimax Strategies", IEEE International Symposium on Signal Processing and Information Technology, pp. 129-132, December, 2008.
- [5] A. Slowik and M. Bialko, "Design and Optimization of IIR Digital Filters with Non-Standard Characteristics Using Particle Swarm Optimization Algorithm", 14<sup>th</sup> IEEE International Conference on Electronics, Circuits and Systems, pp. 162-165, December, 2007.
- [6] J. Sun, W. Fang, W. Chen and W.Xu, "Design of Two-Dimensional IIR Digital Filters Using an Improved Quantum-behaved Particle Swarm Optimization Algorithm", 2008 American Control Conference, pp.2603-2608, June,2008.
- [7] Shing-Tai Pan, Bo-Yu Tsai and Chao-Shun Yang, "Differential Evolution Algorithm on Robust IIR Filter Design and Implementation", Eighth International Conference on Intelligent Systems Design and Application, pp. 537-542, December, 2008.
- [8] Myung-Soon Kim, Dae-Ik Kim, Jin-Gyun Chung and Myung-Sub Lim, et al., "Look-up table based pulse shaping filter design", Electronics Letters, vol. 36, no. 17, pp. 1505-1506, August, 2000.
- [9] R. Storn and K. Price, "Differential evolution—A simple and efficient adaptive scheme for global optimization over continuous spaces," Univ.California, Berkeley, Int. Comput. Sci. Inst., Berkeley, TR-95-012, March 1995. [Online]. Available: <ftp://ftp.icsi.berkeley.edu/pub/techreports/1995/tr-95-012.pdf>.
- [10] S. Das, A. Abraham and A. Konar, "Particle Swarm Optimization and Differential Evolution Algorithms: Technical Analysis, Applications and Hybridization Perspectives", Studies in Computational Intelligence (SCI) 116, 1-38 (2008).
- [11] Y. Shi and R.C. Eberhart (1998), Parameter Selection in Particle Swarm Optimization, Evolutionary Programming VII, Springer, Lecture Notes in Computer Science 1447, 591–600.
- [12] [www.maths.uq.edu.au/MASCOS/MultiAgent04/Fleetwood.pdf](http://www.maths.uq.edu.au/MASCOS/MultiAgent04/Fleetwood.pdf).
- [13] A. Qing, "Electromagnetic inverse scattering of multiple two-dimensional perfectly conducting objects by the differential evolution strategy," IEEE Trans. Antennas Propagat., vol. 51, no. 6, pp. 1251–1262, Jun. 2003
- [14] K. A. Michalski, "Electromagnetic imaging of elliptical-cylindrical conductors and tunnels using a differential evolution algorithm," Microw. Opt. Technol. Lett., vol. 28, no. 3, pp. 164–169, Feb. 2001.
- [15] A. Qing, X. Xu, and Y. B. Gan, "Anisotropy of compos materials with inclusion with orientation preference," IEEE Trans. Antennas Propagat., vol. 53, no. 2, pp. 737–744, Feb. 2005.
- [16] S. Yang, Y. B. Gan, and A. Qing, "Sideband suppression in time modulated linear arrays by the differential evolution algorithm," IEEE Antennas Wireless Propagat. Lett. vol. 1, no. 9, pp. 173–175, Sep. 2002.
- [17] Storn R, Price K. "Differential evolution- A simple and efficient heuristic for global optimization over continuous spaces," J of Global Optimization, pp.341-359, 4 November,1997.
- [18] T.J.Rouphael, RF and Digital Signal Processing for Software-Defined Radio-A multi-standard multi-mode approach, Newnes, pp. 175-191,2009.

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