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Evolutionary Stagnation Avoidance for Design of CSD Coefficient FIR Filters Using GA

Yuto Arie and Kenji Suyama
School of Engineering, Tokyo Denki University,
5 Senju Asahi-cho, Adachi-ku, Tokyo, 120-8551, Japan

Abstract: In this paper, a design method of Canonic Signed Digit (CSD) coefficient Finite Impulse Response (FIR) filters using Genetic Algorithm (GA) is discussed. When applying a general GA, a diversification of search is prevented because the individuals having similar genetic structure increase with increasing search. Therefore, an evolutionary stagnation often occurs. In the proposed method, multiple populations are used to promote the diversification and to avoid the evolutionary stagnation. Several design examples are shown to present the effectiveness of the proposed method.

1. Introduction

Finite Impulse Response (FIR) filters are stable strictly and can realize a linear phase characteristic. On the other hand, the circuit scale tends to be large with increasing a filter order. In general, a multiplier occupies the circuit scale of FIR filters. The multiplier is constructed by shifters and adders. In addition, the number of nonzero digits of filter coefficients correspond to the number of shifters. It is known that Canonic Signed Digit (CSD) representation of filter coefficients is a promising way for a circuit scale reduction[1]. In CSD representation, each digit of filter coefficient is expressed with $\{0,\ 1,\ -1{=}\overline{1}\}$. However, it takes high computational time to design the CSD coefficient FIR filters optimally[2].

Heuristic approaches can calculate a good solution quickly. A lot of design methods of CSD coefficient FIR filter using heuristic approach were proposed[3]-[5]. Among them, Genetic Algorithm (GA) is appropriate to apply to the design problem. Then, because the crossover is carried out based on a difference between individuals, a similar structure of individuals is remained after the crossover.

In this study, the crossover based on a structure of good solution is attempted. Then, one individual is fixed to the best individual. In GA, it is difficult to adjust a balance between the diversification and the intensification. Therefore, when individuals having a similar genetic structure have increased, an evolutionary stagnation tends to occur. In the proposed method, multiple populations are used to promote the diversification. Each the population is specified by the different number of available nonzero digits. The individuals belonging to each population are shared by the crossover and the selection procedure. As a result, it is expected that the evolutionary stagnation can be prevented.

Several design examples are shown to present the effectiveness of the proposed method.

2. Design Problem

A circuit structure of FIR filter is shown in Fig.1. When a filter order N is an even number and an impulse response is even symmetric, a magnitude response $H(\omega)$ is described as following,

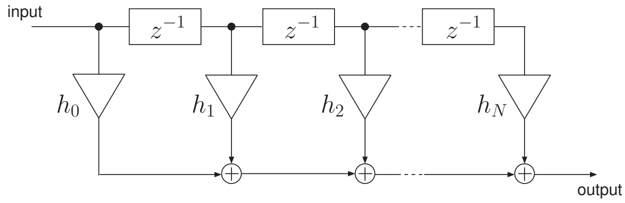

Figure 1. A structure of N-th order FIR filter

$$H(\omega) = \sum_{n=0}^{M}\sum_{k=0}^{p} x_{n,k}2^{-k}\cos n\omega,\ \ x_{n,k} \in \{0, 1, \overline{1}\}, \quad (1)$$

where $M = N/2$, p is a word length, ω is an angular frequency. Then, a phase characteristic becomes the linear phase characteristic.

The fitness function is defined as following,

$$F(\boldsymbol{x}) = W\delta + s_1\phi_1(\boldsymbol{x}) + s_2\phi_2(\boldsymbol{x}), \quad (2)$$

where $\boldsymbol{x} = [x_{0,0}, x_{0,1}, \cdots, x_{M,p}]^T$ is a design parameter vector, W, s_1, s_2 are the weight parameters, δ is maximum error, $\phi_1(\boldsymbol{x})$ and $\phi_2(\boldsymbol{x})$ are penalty functions. $\phi_1(\boldsymbol{x})$ is the penalty function for limiting the number of available nonzero digits in the whole circuit and is defined as following,

$$\phi_1(\boldsymbol{x}) = \begin{cases} 0, & \text{if } \lambda \le \Lambda \\ \lambda - \Lambda, & \text{otherwise} \end{cases}, \quad (3)$$

where

$$\lambda = \sum_{n=0}^{M}\sum_{k=0}^{p} |x_{n,k}|. \quad (4)$$

Λ is the number of available nonzero digits specified in advance. $\phi_2(\boldsymbol{x})$ is the penalty function for forbidding an adjacency of two nonzero digits and is defined as following,

$$\phi_2(\boldsymbol{x}) = \begin{cases} 0, & \text{if } B_{n,k} \le 1,\ \forall n,k \\ \displaystyle\sum_{n=0}^{M}\sum_{k=0}^{p} B_{n,k}, & \text{otherwise} \end{cases}, \quad (5)$$

where

$$B_{n,k} = |x_{n,k}| + |x_{n,k+1}|. \quad (6)$$

The design of CSD coefficient FIR filters is to determine $x_{n,k}$ so as to minimize δ.

It is assumed that a lot of local minimums are involved in this design problem. Although the fitness value of these

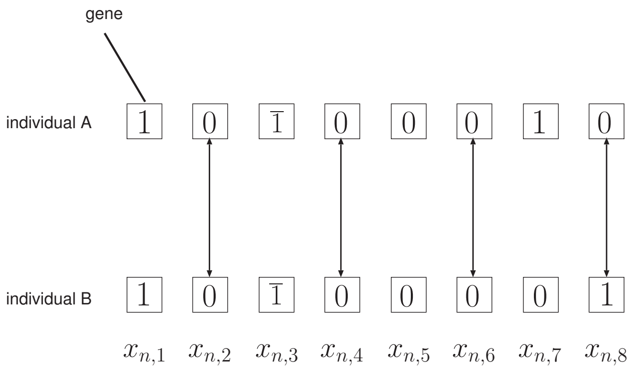

Figure 2. Crossover procedure

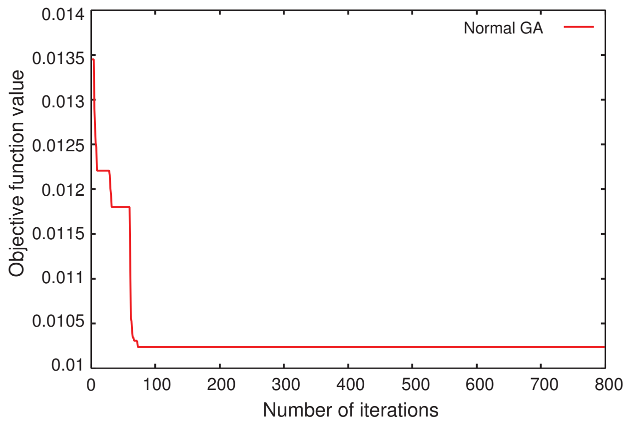

Figure 3. Updating curve of normal GA

local solutions indicate the similar value, these solutions have different structures. Therefore, these solutions whose fitness value is similar value are widely distributed in the solution space.

3. Design of CSD coefficient FIR filters using GA

3.1 Genetic Algorithm

GA is constructed of the crossover, the mutation, and the selection procedure. The j-th individual is expressed as following,

$$\boldsymbol{x}_j = [x_{0,0}, x_{0,1}, \cdots, x_{M,p}]^T. \tag{7}$$

The crossover procedure is shown in Fig.2. In the crossover, two individuals are chosen from the population. The corresponding genes of two individuals are replaced according to a crossover rate. In the mutation, each gene is changed to the allele according to a mutation rate. For example, gene corresponding to 0 changes to 1 or $\bar{1}$ with 50% of probability. In the selection, the individual having the better fitness value is selected, and the other individual is vanished. The diversification is promoted by the crossover and the intensification is promoted by the selection.

3.2 Proposed method

In this study, Proximate Optimality Principle (POP) plays an important role. POP is the principle that good solutions have the similar structure. Each digit of filter coefficient have a similar structure depending on design specifications. Because the best individual has many similar structures with the optimal solution. Therefore, one individual should be fixed for the crossover. Thus, the structure good solutions are held up to the end of search.

Because the crossover is carried out based on a difference between individuals, a similar structure of individuals are remained after the crossover. Then, the evolutionary stagnation occasionally occurs. The updating curve of GA is shown in Fig.3. The solution updating is carried out in early iterations. However, the solution updating is not confirmed in late iterations. In the proposed method, multiple populations are prepared. The multiple populations are for generating the individuals with different structures. The individuals with different structures are shown in Fig.4. Because the individual has a different genetic structure every population, the crossover between the individuals of different structures is carried out with high probability. Then, an individual having a different genetic structure is generated. The difference between multiple populations is the number of available nonzero digits. For the different Λ, similar nonzero allocations appear in the higher digits. On the other hand, in the lower digits, the individual has a different genetic structure. The crossover by using multiple populations is shown in Fig.5. In this crossover, the diversity of population can be improved because the individual having a different structure is generated successively.

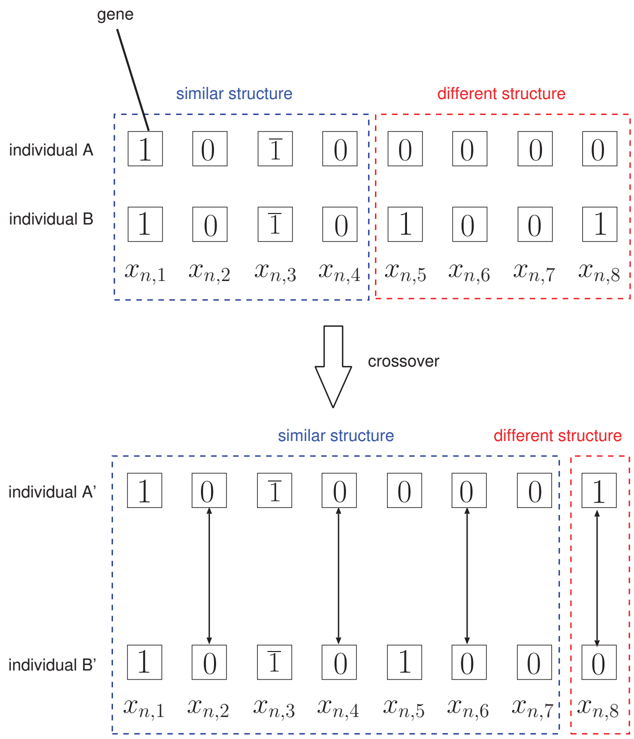

Figure 4. Crossover

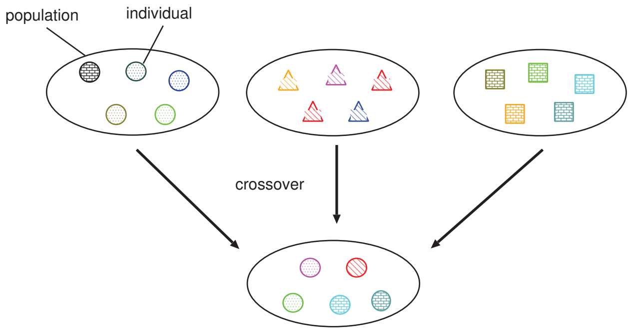

Figure 5. Crossover by multiple populations

Therefore, the evolutionary stagnation can be avoided by the crossover.

In the proposed method, the crossover procedure and the selection procedure are also different from the normal GA. At first, three initial populations are generated from solutions obtained by a Linear Programming (LP) method[7]. Then, the number of available nonzero digits in each population are set to $\Lambda, \Lambda-1$, limitless, respectively. Therefore, different penalty function is posed to each population. Next, the individuals of each population are shared by the crossover. Then, the uniform crossover is applied as the crossover law. In addition, the best individual $\boldsymbol{x}_{\text{best}}$ and $\boldsymbol{x}_{\text{rand}}$ of the individual chosen randomly among all populations are used for the crossover. In the mutation, each gene efficiently changes to the allele. Finally, in the selection, individuals satisfying the constraint are selected from of all populations. Then, the ranking selection is used as the selection law.

4. Design Example

The effectiveness of the proposed method is shown by several design examples. The desired frequency response $D(\omega)$ is given as following,

$$D(\omega) = \begin{cases} 1, & 0 \leq \omega \leq 2\pi f_p \\ 0, & 2\pi f_s \leq \omega \leq \pi \end{cases}, \tag{8}$$

where f_p is a passband normalized edge frequency, f_s is a stopband normalized edge frequency.

Design specifications are listed in Table 1. S is the number of divided frequencies, I is the number of iterations, G is the number of populations, P is the number of individuals in one population, P_c is the crossover rate, P_m is the mutation rate. In GA, P was set to 60, P_c was set to 0.95, P_m was set to 0.1. In the proposed method, G was set to 3. As the initial value, the CSD representations rounded simply from the continuous coefficients obtained by LP were used. The normal GA and 0-1PSO were used as the comparison methods. In 0-1PSO, the number of iteration was set to 800, the number of particles was set to 50 and the other parameters were set according to [8].

Design results are listed from Table 2 to Table 5. In the proposed method, the design errors is smaller than the comparison methods in all design examples. The standard deviation of the proposed method is smaller than the comparison methods in many design examples. Therefore, it can be considered that the proposed method carried out the global search. Because just Ex.1 is $p = 8$, the difference between the best, the average and the worst errors becomes large. In the comparison of standard deviations, the proposed method in Ex.1 is larger than 0-1PSO and normal GA. In Ex.2, the proposed method is larger than 0-1PSO. In the comparison of average error, however, 0-1PSO and normal GA are larger than the proposed method in all design examples. Therefore, it can be considered that 0-1PSO and normal GA search similar bad solutions with high probability.

The magnitude response of Ex.1 is shown Fig.6 and the passband magnitude response is shown Fig.7. From Fig.6 and Fig.7, it is shown that the proposed method can reduce a design error. The updating curve of Ex.4 is shown in Fig.8. From Fig.8, it is shown that the proposed method could carry out the global search.

This design problem

Table 1. Design specifications

	Ex.1	Ex.2	Ex.3	Ex.4
N	50	100	150	200
f_p	0.100	0.220	0.300	0.280
f_s	0.150	0.240	0.315	0.290
p	8	16	16	16
Λ	30	150	200	200
S	250	500	750	1000
I	800	800	800	800

Table 2. Best maximum errors

$\times 10^{-2}$	Ex.1	Ex.2	Ex.3	Ex.4
Proposed GA	1.314	0.955	0.614	0.971
Normal GA	1.478	0.958	0.621	0.984
0-1PSO	1.745	0.978	0.656	1.037

Table 3. Average of maximum errors

$\times 10^{-2}$	Ex.1	Ex.2	Ex.3	Ex.4
Proposed GA	1.562	0.964	0.628	1.019
Normal GA	1.695	0.976	0.642	1.060
0-1PSO	1.945	0.991	0.678	1.193

Table 4. Worst of maximum errors

$\times 10^{-2}$	Ex.1	Ex.2	Ex.3	Ex.4
Proposed GA	1.745	0.979	0.648	1.100
Normal GA	1.975	0.989	0.671	1.216
0-1PSO	2.261	1.002	0.687	1.305

Table 5. Standard deviations

$\times 10^{-3}$	Ex.1	Ex.2	Ex.3	Ex.4
Proposed GA	1.100	0.071	0.066	0.341
Normal GA	0.919	0.095	0.126	0.581
0-1PSO	0.084	0.054	0.097	0.705

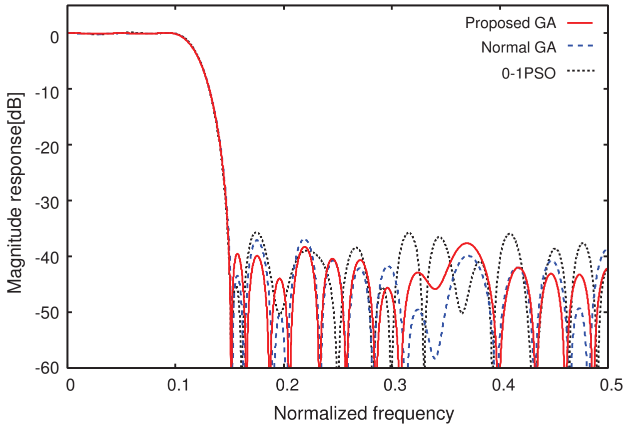

Figure 6. Magnitude response (Ex.1)

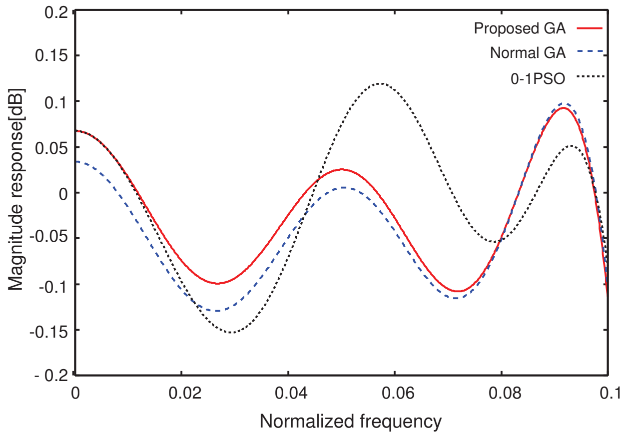

Figure 7. Passband magnitude response (Ex.1)

5. Conclusion

In this paper, the method for designing of CSD coefficient FIR filters by using GA was proposed. In the proposed method, multiple populations were used to promote the diversification and avoid the evolutionary stagnation. Several design examples showed the effectiveness of the proposed method.

References

[1] H. Samueli, “An Improved Search Algorithm for the Design of Multiplierless FIR Filters with Powers-of-Two Coefficients,” IEEE Trans. Circuit and Systems, Vol. 36, No. 7, pp. 1044-1047, July 1989.

[2] N. Takahashi and K. Suyama, “Design of CSD coefficient FIR filters based on branch and bound method,”Proc. of ISCIT2010, pp.575-578, October 2010.

[3] Shing-Tai Pan, “A Canonic-Signed-Digit Coded Genetic Algorithm for Designing Finite Impulse Response Digital Filter,” Digital Signal Processing, Vol.20, pp. 314-327, March 2010.

[4] T. Imaizumi and K. Suyama, “An Effective Allocation of Non-zero Digits for CSD Coefficient FIR Filters using 0-1PSO, ”Proc. of APSIPA ASC 2013, November 2013.

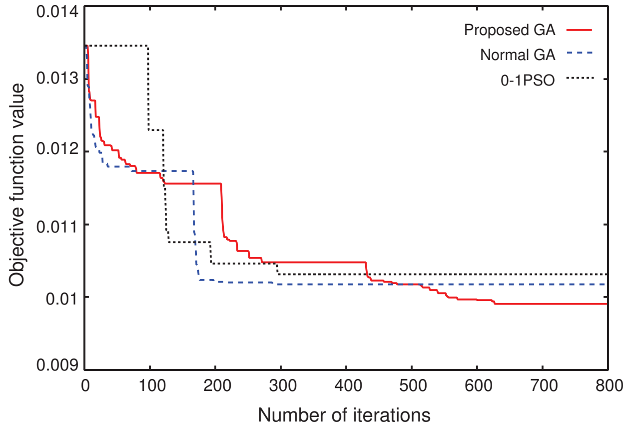

Figure 8. Updating curve (Ex.4)

[5] T. Sasahara and K. Suyama, “An Effectiveness of ACO Approach in Design of CSD Coefficient FIR Filters,”Proc. of ISPACS2015, pp.580-585, November 2015.

[6] F. Ashrafzadeh, “Crossover and Mutation in Genetic Algorithms Employing Canonical Signed-Digit Number System,”Circuits and Systems, pp.702-705, August 1997.

[7] L. Rabiner, “Linear Program Design of Finite Impulse Response(FIR) Digital Filters,” IEEE.Trans. Audio and Electroacoustics, vol. 20, No.4, pp.280-288, October 1972.

[8] T. Imaizumi and K. Suyama, “A Parameter Verification for Design of CSD Coefficient FIR Filters Using 0-1PSO,”IEICE Technical Report, vol113, No.427, CAS2013-72, pp.1-4, February 2014.(in Japanese)