A Uniform-Design Based Multi-objective Adaptive Genetic Algorithm and Its Application to Automated Design of Electronic Circuits

Shuguang Zhao, Xinquan Lai, and Mingying Zhao

School of Electronic Engineering, Xidian University
Xi'an 710071, China

Abstract. The uniform design technique was integrated into an adaptive genetic algorithm for the sake of optimal design of circuits. The approach proposed features a dynamic evaluation mechanism of multi-objectives, an efficient encoding-decoding scheme based on preferred values, and a classified adaptation strategy of genetic parameters. It was validated by experiments.

1 Introduction

Circuit design is a typical problem of multi-objective optimization. A fitness function in the form of *weighted sum of the objective functions* was frequently used in solving such a problem with an evolutionary algorithm (EA) [1-4]. However, it confines a host EA to just one search direction implied by the weight vector and at most one Pareto-optimal solution per run, preventing the EA from obtaining uniformly distributed solutions. Treating less important objectives as constraints leads to similar faults [2-4]. Considering that multiple Pareto-optimal solutions could be obtained by using specific weight-vectors which suggest multiple search directions uniformly directed at the Pareto-frontier, we have developed a multi-objective adaptive genetic algorithm (UMOAGA) based on the Uniform Design Technique (UDT) [5] and our previous works [1]. The UMOAGA was introduced and verified hereafter.

2 UDT Based Fitness Functions and Crossover Operators

The UDT is a useful technique in experiment design, which can select q representative combinations from q^n combinations resulted from n factors and q levels. As the q combinations are generally related with q points uniformly scattered in the combination space, the components of a weight vector (i.e., weight coefficients) derived from them may have expected proportion relationships with each other in the sense of uniformity and integrality [3]. Thus, to compose m fitness functions for k objective functions, we can form a *uniform design matrix*, $\boldsymbol{U}(k,m)=[\boldsymbol{U}_{i,j}]_{m\times k}$, by looking up the UDT tables [5] and use it in the following way,

$$w_{i,j} = U_{i,j} / \sum_{j=1}^{k} U_{i,j} \quad i = 1,\cdots,m, \quad j = 1,\cdots,k \tag{1}$$

L. Jiao et al. (Eds.): ICNC 2006, Part I, LNCS 4221, pp. 653 – 656, 2006.

Then, m normalized fitness functions can be composed as follows, each of which will be used to update $1/m$ of the population so as to let the UMOAGA search in m uniformly scattered directions towards the Pareto frontier,

$$fit_i = \sum_{j=1}^{k} w_{i,j} \cdot f_j(X), \quad i = 1, \cdots, m \tag{2}$$

The UDT was also applied to the crossover operation. In contrast with traditional ones imitating zoogamy, the UDT based crossover operators we designed choose and mate multiple individuals to make multiple offspring. For a binary-coded GA whose individuals are encoded as $P_i = b_{i,1} \& b_{i,2} \ldots \& b_{i,L}$, $b_{i,j} \in \{0,1\}$, the multi-parent crossover operation can be briefly explained as follows: (1) After determining the number of parents, m, choose a natural number, $n<m$. Look up the UDT tables to obtain a *uniform design matrix*, $\boldsymbol{U}(n,m) = [\boldsymbol{U}_{i,j}]_{m \times n}$. (2) Randomly divide the set of individuals′ subscript into n subsets, S_i, which satisfies $S_i \cap S_j = \phi$ for $i \neq j$ and $\cup_i S_i = S$, $i=1\ldots n$. (3) Randomly choose m parents in a proper manner. Sort them in a degressive order of fitness. Relate each of them with its sequence number ranges from 1 to m. (4) Iteratively produce m offspring with a exclusive row of $\boldsymbol{U}(n,m)$ each time. For the ith offspring, cope the jth partition of the parent indicated by the element $\boldsymbol{U}_{i,j}$ as its jth partition, referring to subset S_j that prompts the subscripts involved.

As to a real-coded or integer-coded GA, the multi-parent crossover operation is similar to that mentioned above. But each of m offspring is produced by computing a weighted sum of n parents on the basis of $\boldsymbol{U}(n,m)$, as shown in Equation (3).

$$X_i^{'} = \sum_{j=1}^{n} (U_{i,j} \bullet X_j) / \sum_{j=1}^{n} U_{i,j} \quad i = 1, \cdots, m \tag{3}$$

3 Representing Scheme and Parameters Adaptation Strategy

Based on a few restrictions on circuit construction other than a fixed topological structure, an individual in the UMOAGA is encoded in a format like a net-list, e.g.,

$$C_i = [type_i, node1_i, node2_i, walue_i] \tag{4}$$

Where $type_i$, $node1_i$, $node2_i$ and $value_i$ denote the type, the (two) nodes connected and the value of the ith component, respectively. The components′ values are deliberately encoded with *preferred values* (e.g., a 1% precision series using just 96 numbers to span a value interval of one decade) commonly used with discrete components, in order to get a shorter chromosome (e.g., 9 bits other than 18 bits for a component value between 1 and 10^5) and accordingly less computation amount and more effective results. Moreover, the crossover probability P_c and the mutation probability P_m are allowed to vary with the individual diversity, which is estimated as

$$f_d(t) = fit_{avg}(t) \,/\, [\, \varepsilon + fit_{max}(t) - fit_{min}(t)] \tag{5}$$

Where $fit_{avg}(t)$, $fit_{max}(t)$ and $fit_{min}(t)$ are the average, maximum and minimum fitness of the individuals, respectively**.** The P_c is allowed to adapt in the following way

$$P_c(t) = P_{c0} \cdot \exp(-b_1 \cdot t / t_{\mathrm{m}}) \,/\, f_d(t) \tag{6}$$

Because genes of different categories usually have distinct effects on the circuit performances, two distinct adaptation rules are designed for the P_m as follows

$$P_{ms}(t)=P_{ms0} \cdot \exp(-b_2 \cdot t / t_m) \cdot f_d(t) \tag{7}$$

$$P_{mv}(t)=\begin{cases} 0 & t<t_0 \\ P_{mv0}\cdot[1-e^{-b_3\cdot(t-t_0)/t_{\max}}]\cdot f_d(t) & t_0 \le t < t_1 \\ P_{mv0}\cdot[e^{-b_3\cdot(t-t_1)/t_{\max}}-e^{-b_3\cdot(t-t_0)/t_{\max}}]\cdot f_d(t) & t_1 \le t < t_m \end{cases} \tag{8}$$

Where $P_{mv}(t)$ is assigned to those related to component values (i.e., $value_i$), $P_{ms}(t)$ is assigned to others, t_m is the allowed generation number, and the other terms are positive constants. With the above multi-stage adaptation strategy, the UMOAGA can be expected to generate and optimize the circuits automatically.

4 Experimental Results and Conclusions

With the UMOAGA, some experiments on active filters were completed successfully, using Pspice simulation based fitness evaluation [1]. For example, an experiment on low-pass active filters was performed with the following restriction to the circuit scale: one operational amplifier, no more than 8 nodes (as shown in Fig. 1) and no more than 15 resistors or capacitors. The four objective functions to be minimized are: relative error of transition frequency, $f_1 = |f_c - f_{co}|/f_{co}$, where f_{co} and f_c are the

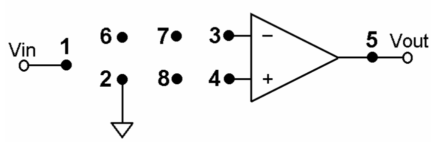

Fig. 1. The circuit framework used in the experiments on active filters

Table 1. Some experimental results on a low-pass active filter (f_{co}=2kHz, G_0=20dB, G_s=-60dB)

No.	Simplified chromosomes of the evolved circuits	Objective values
1	[R,1,6,2.20K], [C,6,2,51.0nF], [R,3,6,22.0K], [C,5,3,200pF], [R,5,6,22.0K]	f_1 =0.13, f_2 =10.5 f_3 =0.05, $\mathbf{f_4}$ **=6**
2	[R,1,6,1.20K], [C,2,6,62.0nF], [R,6,3,5.10K], [C,3,5,22.0nF], [R,5,6,5.10K], [R,4,2,5.10K], [R,4,5,51.0K]	$\mathbf{f_1}$ **=0.01**, f_2 =8.2 f_3 =0.11, f_4 =8
3	[R,1,6,330], [C,2,6,1.0uF], [R,6,7,750], [C,7,2,43.0nF], [C,3,5,1.0nF], [R,3,7,5.10K], [R,7,5,5.10K], [R,4,5,47.0K], [R,4,2,4.70K]	f_1 =0.07, f_2 =3.7 $\mathbf{f_3}$ **=0.02**, f_4 =10
4	[R,1,7,2.20K], [C,7,2,360nF], [R,7,6,22.0K], [R,6,4,20.0K], [C,4,2,9.10nF], [C,5,6,2.00nF], [R,2,3,22.0K], [R,3,5,200K]	f_1 =0.12, $\mathbf{f_2}$ **=1.1** f_3 =0.35, f_4 =9

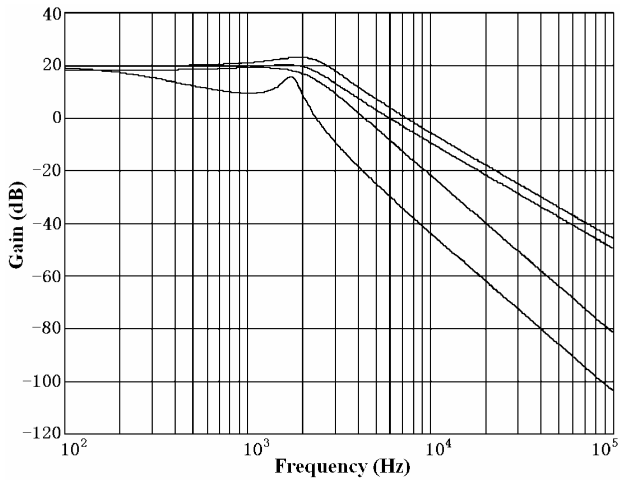

Fig. 2. Amplitude-frequency response curves of the filters listed in Table 1

expected and actual transition frequency, respectively; pass-band undulation, $f_2 = |G_{max} - G_{min}|/G_0$, where G_{max}, G_{min} and G_0 are maximum, minimum and the expected *Gain* in the pass-band, respectively; relative bandwidth of the transition-band, $f_3 = |f_s - f_c|/f_c$, where f_s is the first frequency with the expected attenuation, G_s; circuit complexity, f_4 = *number of the components*. With a uniform design array, ***U***(4,5), a set of effective circuits were evolved, as illustrated in Table 1 and Fig. 2. These results suggest that the UMOAGA can be expected to automatically searching out a set of Pareto-optimal solutions or effective circuits in accordance with multiple objectives.

References

1. Zhao, S.: Study of the evolutionary design methods of electronic circuits. PhD dissertation (in Chinese). Xidian University, Xi′an (2003)
2. Fonseca C. M., Fleming P. J.: An overview of evolutionary algorithms in multi-objective optimization. Evolutionary Computation 1 (1995) 1–16
3. Leung Y.W., Wang Y. P.: Multiobjective programming using uniform design and genetic algorithm. IEEE Trans. on System Man and Cybernetics–Part C 3 (2000) 293–304
4. Coello Coello C. A.: An Updated Survey of GA-Based Multiobjective Optimization Techniques. ACM Computing Surveys 2 (2000) 109–143
5. Fang K. T., Ma C. X.: Orthogonal and Uniform Experiment Design (in Chinese). Science Press, Beijing (2001)