Composite differential evolution for optimal length low-dispersion fiber Bragg gratings

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This paper presents the design of a low-dispersion fiber Bragg Grating (FBG) with an optimal grating length. The paper aims to develop a numerical solution for the low-dispersion fiber Bragg Grating (FBG) via a variation of differential evolution, which is called CoDE. A novel objective function formulation is used to the optimal grating length low-dispersion FBG design. CoDE combines several effective trail vector generation strategies with some suitable control parameter settings in a random way to generate trail vectors. The design of a low-dispersion FBG filter with 25-GHz bandwidth is considered. The experimental results of the CoDE algorithm have been shown better than the CMAES algorithm and PSO algorithm in a statistically meaningful way.

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1. Introduction

Fiber Bragg grating has an important role in diverse fields ranging from optical communications to optical sensing. The synthesis and fabrication of FBGs have recently attracted many researchers [1]. Many methodologies have been proposed to solve the FBG in the literature [2-10]. Most of the previous approaches for the design of low-dispersion FBGs are based on the layer peeling inverse scattering algorithm. However, in practice, the FBGs designed using the methods to achieve the best performance generally has complicated index modulation profiles and long grating lengths. Moreover, for short grating with small bandwidths (BWs), the unwanted tail can be significant and lead to large deviation between the realized and target spectra [11]. In practice, they are more practical and easier to fabricate with good quality than longer gratings. Therefore, it is desirable to use other efficient approaches to design shorter-grating FBG filter with small BW.

Recently, different global optimizations have been successfully used to find the optimal index profiles to satisfy the prescribed filter specifications. The heuristic optimizations techniques such as genetic algorithm (GA), particle swarm optimization (PSO), evolutionary programming (EP), and Tabu search have been proposed to accurately solve FBG filter. In [12], S. Bashar propose a novel formulation of the objective function for the design of fiber Bragg grating based filters with respect to the given design specifications. Particle swarm optimization technique is employed here to find an optimum index modulation profile that meets the target design. In order to demonstrate the effectiveness of the PSO, an optimal design of a low-dispersion FBG-based filter with 0.2nm bandwidth is considered as the experiment. In [11], S. Bashar uses covariance matrix adapted evolution strategy to design a low-dispersion fiber Bragg grating with an optimal grating length. Experimental results show the CMAES algorithm is very appropriate for the practical design of length optimized FBG-filter.

Particularly, Differential evolution (DE) [13] is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. DE is a simple yet powerful population based, direct search algorithm with the generation and test feature for global optimization problems. The basic idea of DE is to create new candidate solutions by combining the parent individual and several other individuals of the same population, and a candidate solution replaces the parent only if it has better fitness. Previous work shows the differential evolution to be an effective algorithm for some kind of problems. Furthermore, the differential evolution is well suitable to solve this problem because of the algorithm is easier to implement than GA and applied design problem with both discrete and continuous design parameters. In order to solve these problems, several variations of DE have been proposed to enhance the performance of the standard DE recently. Ranhnamayan et al [14] proposed an opposition based differential evolution, as called ODE. The ODE algorithm consisted of a DE framework and two opposition based components: the former after the initial sampling and the latter after the survivor selection scheme. Qin and Suganthan [15] proposed a self adaptive DE algorithm (SaDE), in which both trail vector generation strategies and the associated control parameter values were gradually self-adaptive by learning from their previous experiences when generating promising solutions. Wang [16] proposed a novel method, called composite DE (CoDE), which used three trail vector generation strategies and three control parameter settings.

In this letter, composite differential evolution (CoDE) is used to design of a low-dispersion FBG filter with an optimal grating length. The optimal–length FBG filter design is proposed based on six design specifications: 3-dB BW, sidelobe level (SLL), first null Bandwidth (FNBW), in-band ripple (Rrip), maximum reflective power (Rmax), and in-band group delay ripple (trip). The proposed optimum-length low-dispersion FBG design determines the optimal grating length that satisfies the specified performance indicators. To demonstrate the capability of the CoDE algorithm and the effective of the objective function, a comparison between optimized performance indicators generated by various algorithms is shown.

2. Problem formulation

A simple FBG model is divided into n piecewise uniform sections. The transfer matrix for the entire grating can be obtained by chain multiplying the individual transfer matrices of the grating sections. The total grating length (L_g) is equal to *n*l*. A uniform section of length (*l*) is determined by the optimization algorithm to find the optimal grating length for the desired reflective spectrum and dispersion profile. Hence, in this letter, the objective of the optimal length low-dispersion FBG filter design problem is to find an index modulation profile correspond to n equal-length uniform sections and the section length (*l*). Then, the total variable of this problem is *n*+1.

In general, evolutionary algorithms use the concept of fitness to represent whether the solution is suitable to the design the objective. In the FBG synthesis problem, the cost function can be represented by the sum of the weighted errors. In order to show better performance, suitable weighting factor values at each wavelength are to be chosen [12]. The desired reflective spectrum and the group delay characteristics are predefined using six specifications: first null bandwidth (FNBW), sidelobe level (SLL), allowed in-band ripple in the reflective spectrum (Rrip), maximum reflective power (Rmax), and in-band group delay ripple (Trip) [11]. Then, for the design of an optimal-length low-dispersion FBG filter, the following fitness function [11] can be described as follow:

$$\begin{aligned} F &= (FNBW_d - FNBW)^2 + (BW_d - BW)^2 \\ &+ g(Rrip_d - Rrip) + g(SLL_d - SLL) \\ &+ (R\max{}_d - R\max)^2 + a * g(Tripd - Trip) + b * L_g \end{aligned} \tag{1}$$

$$g(x) = \begin{cases} 0 & \text{if } x \ge 0 \\ x^2 & \text{otherwise} \end{cases} \tag{2}$$

Where the subscript *d* is the target values of the design specifications. The first five terms in the fitness function (1) does not require the weighting factors for the errors in the reflective spectrum for different wavelength and the last two terms correspond to minimizing the in-band group delay ripple and the total grating length. *a* determines how the reflective spectrum is weighted with respect to the phase or group delay response and is set 0.2. The value of *b* is 0.01. For a fixed-length FBG Filter design, the last term L_g is not included in the objective function. The typical target design specifications used in our simulations are: SLL of -40dB, BW of 0.2nm, FNBM of 0.25nm, Rrip of 0.5dB, Trip of 0.5ps and Rmax of 0.99.

3. Composite differential evolution

Differential Evolution (DE) is an Evolutionary Algorithm first introduced by Storn and Price [13]. Similar to other evolutionary algorithms particularly genetic algorithm, DE uses some evolutionary operators like selection recombination and mutation operators. Different from genetic algorithm, DE use distance and direction information from current population to guide the search process. The crucial idea behind DE is a scheme for producing trial vectors according to the manipulation of target vector and difference vector. If the trail vector yields a lower fitness than a predetermined population member, the newly trail vector will be accepted and be compared in the following generation.

Wang et al [16] proposed a new composite DE, CoDE, which is combining several effective trail vector generation strategies with some suitable control parameter settings in a random way to generate trail vectors. This algorithm has a simple structure and is easy to implement. This basic idea of the algorithm is to randomly combine several trail vector generation strategies with a number of control parameter settings at each generation to create the new trail vector. The above idea is illustrated in Fig. 1. In the paper, the author chooses three trail vector generation strategies and three control parameter settings to constitute the strategy candidate pool and the parameter candidate pool, respectively. The three selected trail generation strategies are:

(1) “rand/1/bin”
(2) “ rand/2/bin” and
(3) “current-to-rand/1”

Note that the “current-to-rand/1” strategy, the binominal crossover operator is not applied. The three control parameter settings are:

(1) [F=1.0, Cr=0.3]
(2) [F=1.0, Cr=0.9]
(3) [F=0.8, Cr=0.2]

The three strategies and three parameter settings are frequently used in many DE variant and the properties have been discussed in [16]. At each generation, each trail vector in strategy candidate pool is used to create a new trail vector with a control parameter setting randomly chosen from the parameter candidate pool. Then three trail vectors are generated for each target vector. The best ones enter the next generation if it better than its target vector. The pseudo code of CoDE is presented as follow:

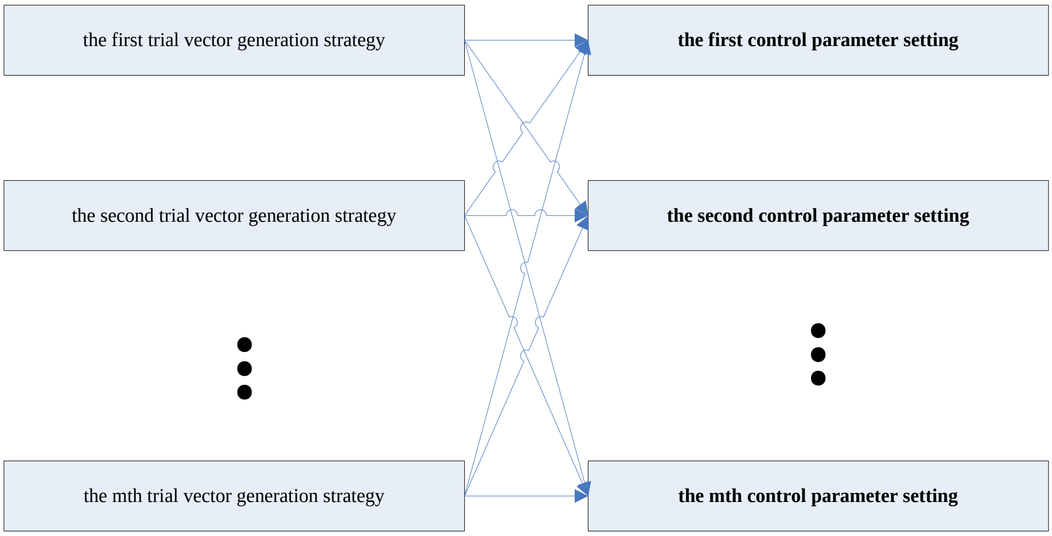

Fig. 1. Illustration of combining trial vector generation strategies with control parameter settings.

3. Experimental results

This section compares the performance of CoDE over two different design problems: the design of a fixed length low-dispersion FBG filter and the design of an optimal length low-dispersion FBG filter with 0.2-nm BW for both designs are considered. The center wavelength of the filter is set to be $\lambda^c = 1550$ nm. For the design of the fixed-length low dispersion FBG filter, the total grating length and number uniform sections are fixed at 40mm and 20 as in [8]. For the optimal-length low dispersion FBG filter, each section length is varied between 1 and 2.5 mm. The index profile is constrained to take value between $-3e^{-4}$ to $3e^{-4}$. For testing the consistency of the CoDE algorithm, 30 independent runs were conducted with 20000 function evaluations. The computation time required for 20, 30 and 40 sections were 101.24, 144.54 and 180.96 seconds on an Intel(R) Core(TM) 2 Quad 2.83-GHz machine.

3.1 Fixed-length low-dispersion FBG filter design

For the fixed-length low-dispersion FBG filter, the results of all the 30 runs satisfy the specifications of the reflective spectrum and the group-delay response. The results can be found in Table 1. As can be seen in Table 1, The CoDE can perform better solutions than other algorithms. The best performance of the in-band group-delay ripple is 0.0468 mean performance of the group-delay ripple is 0.2458 worst performance of the group-delay ripple is 0.962. The value obtained from the simulation for the various design specifications namely the FNBW, BW, Rrip, SLL, and Trip, are 0.25nm, 0.2nm, 0.2dB, -40dBm and 0.0468os, respectively. The in-band reflective power was found to be at 99%. The in-band group delay varies between 223.1239 and 223.1706. The in-band dispersion length varies between +18 to -18 ps/nm. For the same grating length and index modulation strength, in [6], the filter has more than -10-dB SLL in the reflective spectrum and has the worst in band dispersion value of 300ps/nm. In [8], it was found that the maximum in-band dispersion of 6000ps/nm.

Table 1. Optimal Grating length for differential number of sections.

Performance	Optimum grating length(mm)		
	20 Sections	30 Sections	40 Sections
Best	**32.86**	**30.01**	**30.8394**
Median	33.56	30.82	32.68
Worst	34.23	33.45	35.26
Std deviation	0.536	0.681	0.964

3.2 Optimal-length low-dispersion FBG filter design

In this work, the grating length is also contained as one of the design parameters without compromising on the low-dispersion target specifications used in the previous section. The optimal grating length needs to satisfy the reflective and group delay specification is determined. The best, median, worst and standard deviation of the optimal grating length for different algorithms obtained in 30 runs are listed in Table 1. The results are all satisfied the specification corresponding to the reflective spectrum and the group delay response. From the Table 1, we can find that the CoDE emerged the best candidate algorithm for the best, mean, and worst value.

***procedure** Algorithm description of CoDE algorithm*

begin

Control parameter:

NP: the number of individuals at each generation.

Max_FES: maximum number of function evaluation evaluations.

The strategy candidate pool: "rand/1/bin", "rand/2/bin", "current-to-rand/1"

The parameter candidate pool: [F=1.0, Cr=0.3], [F=1.0, Cr=0.9], and [F=0.8, Cr=0.2]

***Step 1)** Initialization*

***Step 1.1)** Set the current generation number G=0;*

***Step 1.2)** Generate an initialize population $x_{1,0},\cdots,x_{NP,0}$ by uniformly and randomly sampling from the feasible solution space.*

***Step 1.3)** Evaluate the objective function values of these points*

***Step 1.4)** FES=NP*

***Step 2)** For $i=1,\cdots,NP$,do*

***Step 2.1)** use the three strategies, each with a control parameter setting randomly selected from the parameter pool, to generate three trail vectors $u_{i\_1,G}$, $u_{i\_2,G}$, and $u_{i\_3,G}$ for the target vector $x_{i,G}$.*

***Step 2.2)** Evaluate the objective function values of three trail vectors $u_{i\_1,G}$, $u_{i\_2,G}$, and $u_{i\_3,G}$;*

***Step 2.3)** Choose the best trail vector (denoted as $u^*_{i,G}$) from the three trail vectors $u_{i\_1,G}$, $u_{i\_2,G}$, and $u_{i\_3,G}$*

***Step 2.4)** Selection and replacement:*

$$x_{i,G+1}=\begin{cases}u_{i,G}, f(u_{i,G})<f(x_{i,G})\\ x_{i,G}, otherwise\end{cases}$$

***Step 2.5)** Set FES=FES+3*

***Step 3)** If FES<= Max_FES, stop and output the vector with the small objective function value in the population, otherwise, set G=G+1 and go to Step 2.*

end

The results show that the grating length need to achieve the given reflective and group delay specification is 32.86 for 20 sections, and 30.83 for 40 sections. Compared with the fixed length, the same specification is approximately 37%. Fig. 2 and Fig. 3 show the index modulation profile, reflective spectrum of the optimal-length low-dispersion FBG filter for 20 sections and 30 sections. In Table 2, we compared our results with several other optimization methods for 0.2nm BW. Other methods [3],[5],[11] and [12] that shown different BWs of 0.4 and 0.5nm are not used in comparison.

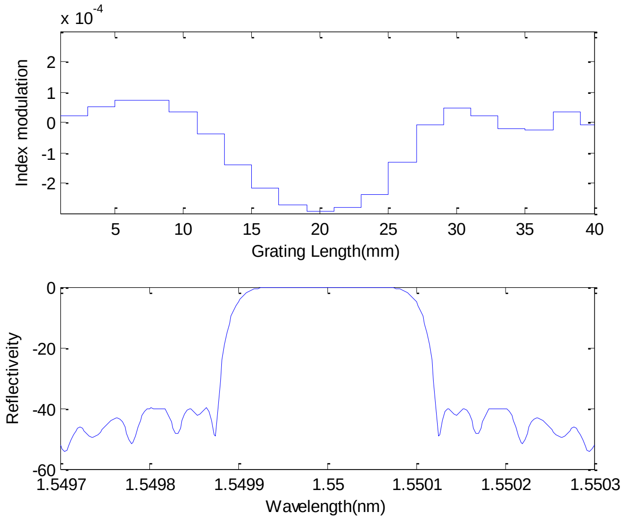

Fig. 2. Designed optimal-length low dispersion FBG filter of 20 sections.

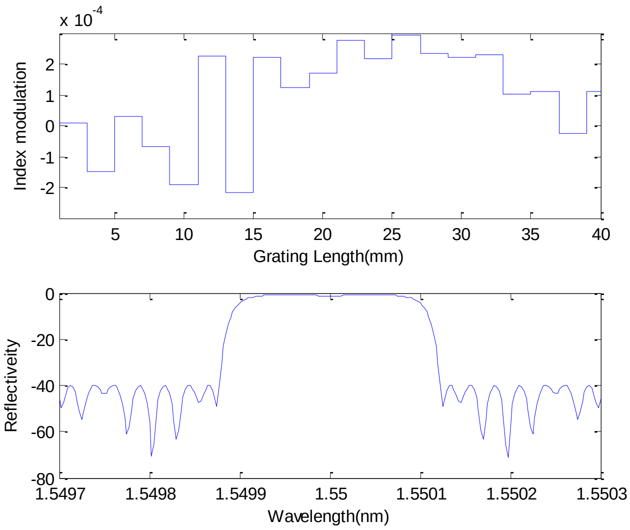

Fig. 3. Designed optimal-length low dispersion FBG filter of 40sections.

Table 2. Comparison of various optimum FBG parameters.

Parameter	CODE Fix length	Len.20 sections		Len.3 sections		Len.4 sections		PSO[12]	Ref[8]	Ref[9]	Ref
		CMAES[11]	CoDE	CMAES[11]	CoDE	CMAES[11]	CoDE				
Length	40	32.96	**32.86**	30.04	**30.01**	29.20	**30.8394**	40	31	40	35.6
FNBW	0.25	0.25	**0.25**	0.25	**0.25**	0.25	**0.25**	0.25	-	-	0.4
SLL	-40	-40.02	**-40**	-40	**-40**	-40.127	**-40.001**	-40	-10	-	-28
Rrip	0.2	0.365	**0.2864**	0.3878	**0.4824**	0.485	**0.4989**	0.2549	-	-	0.1
Trip	0.0468	0.134	**0.1126**	0.29	**0.2235**	0.424	**0.2989**	0.4495	-	-	1
IBD	18	29.5	**46.6**	43.56	**49.31**	60.34	**47.1**	56.4	300	6000	30
GD	223	207.2	**139**	152.2	**176**	166.5	**192**	250	-	-	125

4. Conclusions

In this work, the design of optimal-length low-dispersion FBG filters using the CoDE algorithm has been presented. A novel objective function has been used to incorporate the grating length as a novel parameter in the optimization process. The design of a narrow-BW FBG filter with 0.2 nm BW has been presented. The experimental results clearly indicate superior performance of the proposed algorithm in comparison to some recent optimization algorithms. The result clearly shows that the CoDE method is well suitable for the design of optimal-length low-dispersion FBG filter. We hope that this paper sparks a new venue of research in the problem of solving optimal-length low-dispersion FBG filter.

References

[1] T. Erdogan, J. Lightw. Technol., **15**, 1277 (1997).
[2] M. C. Parker, R. J. Mears, S. D. Walker, J. Opt. A, Pure Appl. Opt., **3**, 171(2001).
[3] E. Peral, J. Capmany, J. Marti, IEEE J. Quantum Electron., **32**, 2078 (1996).
[4] L. Poladian, Opt. Lett., **25**, 747(2000).
[5] R. Feced, M. N. Zervas, A. Muriel, IEEE J. Quantum Electron., **35**(8), 1105 (1999).
[6] J. Skaar, O. H. Waagaard, IEEE J. Quantum Electron., **39**, 1238 (2003).
[7] J. Skaar, K. M. Risvik, J. Lightw. Technol., **16**, 1928 (1998).
[8] C. L. Lee, Y. C. Lai, Opt. Commun., **235**, 99 (2004).
[9] N. Q. Ngo, R. T. Zheng, S. C. Tjin, S. Y. Li, Opt. Commun., **241**, 79 (2004).
[10] S. Manos, L. Poladian, 8-12, 2089 (2003).
[11] S. Baskar, A. Alphones, P. N. Suganthan, N. Q. Ngo, R. T. Zheng, IEEE Photonics Technology Letters, **17**, 2119 (2005).
[12] S. Baskar, R. T. Zheng, A. Alphones, N. Q. Ngo, P. N. Suganthan, IEEE Photonics Technology Letters, **17**, 615 (2005).
[13] R. Storn, Journal of Global Optimization. **11**, 341 (1997).
[14] S. Rahnamayan, H. R. Tizhoosh, M. M. A. Salama, IEEE Transactions on Evolutionary Computation, **12**, 64 (2008).
[15] A. K. Qin, V. L. Huang, P. N. Suganthan, IEEE Transactions on Evolutionary Computation, **3**, 398 (2009).
[16] Y. Wang, Z. X. Cai, Q. F. Zhang. IEEE Transactions on Evolutionary Computation, **15**(1), 55 (2011).

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