Fiber Bragg Optimization Using Parallel Processing and Genetic Algorithm

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ABSTRACT

In this work are presented two designs of fiber Bragg gratings optimized by using genetic algorithm and parallel processing. The results achieved show the robustness of that technique when applied to complex search spaces. Besides, it is shown that the use of the parallel processing improves the performance of genetic algorithm.

Keywords: Genetic Algorithm, Optical Devices, FBG, MPI

1. INTRODUCTION

There are many problems, which may be solved using a Genetic Algorithm (GA). An interesting application that has been investigated is the optimization of fiber Bragg gratings. This technique was chosen because its peculiar characteristics instead of other traditional optimization methods.

In this work traditional techniques are considered as techniques, which need an initial guess to start the optimization process. Because of the complex search space found in such problems, which is composed by discontinuity, nonlinearity and multimodality, traditional techniques require a previous knowledge about the search space to launch the initial guess as close as possible of the global optimum, otherwise the optimization process "stuck" at the first extreme and the solution found will be a local optimum. In real world problems the previous knowledge about the search space is a difficulty task, requiring auxiliary techniques to provide an initial solution[1-2]. These characteristics have encouraged the use and the development of robust techniques in order to overcome these adversities. On the other hand, Genetic Algorithms are able to find feasible solutions for grating structures without needing an initial guess and the results achieved by this method may be improved by traditional techniques.

In order to improve the efficiency of optimization process, the genetic algorithm was paralleled. The parallel technique used was the Message Passing Interface (MPI) that allows the software to run on different architectures, possibly, with different operating systems.

This work is structured as follows: Section II presents Bragg gratings and Genetic Algorithm theory. In section III the paralleling process applied to Genetic Algorithm is described. In section IV are shown the results achieved and finally, conclusions are presented at section V.

2. BRAGG GRATING AND GENETIC ALGORITHMS

A. GENETIC ALGORITHMS

Genetic algorithms (GAs) are optimization algorithms that simulate the natural selection and natural genetics principles[2-9].

The basic principle consists of evolving a set of initial solutions toward the optimal point. When the optimization process finishes the best solution is picked up and can be used as starting design at traditional methods in order to refine the solution.

GAs have some particular characteristics, which make them different from most of the traditional optimization

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methods:

- These algorithms do not start the search from a single point (as traditional methods do), but from a set of points;
- GAs do not use derivatives;
- GAs use probabilistic transition rules instead of deterministic rules.

Because of these characteristics Genetic Algorithms are a powerful technique to be used at problems, in which the search space is too complex. GAs search the region of the global optimum in a function f(X), where X is defined as $X=\{X_L|L=1,2,...N\}$, N is the number of variables and X_L ranges from X_{Lmin} to X_{Lmax}.

During the optimization process GAs in their simplest form have at least three basic operations designated as selection, crossover and mutation, each one of them plays an important role along of the optimization.

An important aspect of GAs is the fitness function, which evaluates the quality of a solution as measurement for the chromosome's performance and at the same time represents the connection between the physical problem and the Genetic Algorithm.

This paper uses a fitness function given by

$$F(\mathbf{X}) = \left(\frac{1}{p} \sum_{j=1}^{p} \left\{ \left[r(\lambda_j) - r_{opt}(\lambda_j) \right] \right\}^2 \right)^{-1} \tag{1}$$

$r(\lambda_i)$ and $r_{opt}(\lambda_i)$ are reflectivity calculated and desired, respectively. The variable p stands for the number of samples at fitness function.

B. BRAGG GRATINGS

In this paper are considered reflection gratings, in which the coupling occurs between modes traveling at opposite directions. The analyze of such structures is based on coupled mode theory[10], where the coupling equations and the synchronous approximation are used in order to obtain the coupling coefficients given by

$$k = k^* = \frac{\pi}{\lambda} v \bar{\delta}_{neff} \tag{2}$$

$$\hat{\sigma} = \delta + \sigma - \frac{1}{2}\frac{d\phi}{dz} \tag{3}$$

$$\sigma = \frac{2\pi}{\lambda} \bar{\delta}_{neff} \tag{4}$$

At expressions (2)-(4) δ means the detuning, k is the AC coupling and $\hat{\sigma}$ is the general self-coupling coefficient, σ stands for the dc coupling. $\bar{\delta}_{neff}$ is the index change spatially average over a grating period (Λ), ϕ is the grating chirp along of z and v is the fringe visibility of index change.

A matrix method can be used at modeling nonuniform gratings, which consists of dividing a nonuniform grating in M piecewise-uniform sections where each section is represented by a 2x2 matrix, thus these matrices are multiplied in order to describe the whole grating. Fig. 1 illustrates this method.

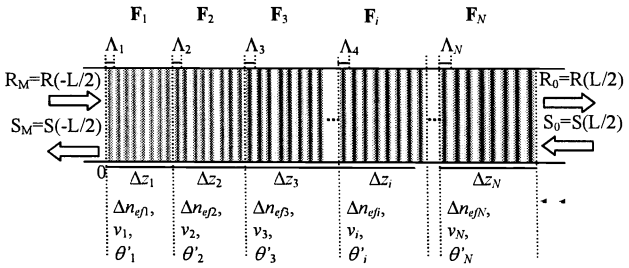

Fig. 1: Bragg grating divided in M uniform sections

Defining R_i e S_i as output amplitudes at interface of each uniform section i, the boundary conditions are given by

$R_0=R(L/2)=1$ e $S_0=S(L/2)=0$ and the field amplitudes at section M are $R(-L/2)=R_M$ e $S(-L/2)=S_M$. The propagation through each uniform section i is described by a matrix F_i, defined as

$$\begin{bmatrix} R_i \\ S_i \end{bmatrix} = F_i \begin{bmatrix} R_{i-1} \\ S_{i-1} \end{bmatrix} \tag{5}$$

For Bragg gratings the matrix F_i is given by

$$F_i = \begin{bmatrix} \cosh(\gamma_B \Delta z) - i\frac{\hat{\sigma}}{\gamma_B}\sinh(\gamma_B \Delta z) & -i\frac{\kappa}{\gamma_B}\sinh(\gamma_B \Delta z) \\ i\frac{\kappa}{\gamma_B}\sinh(\gamma_B \Delta z) & \cosh(\gamma_B \Delta z) + i\frac{\hat{\sigma}}{\gamma_B}\sinh(\gamma_B \Delta z) \end{bmatrix} \tag{6}$$

For the ith uniform section Δz is the length of the section, $\hat{\sigma}$ and κ are the local values for the coupling coefficients, and

$$\gamma_B = \sqrt{\kappa^2 - \hat{\sigma}^2} \tag{7}$$

The output amplitudes can be derived multiplying the matrices of the individual sections[10], so that

$$\begin{bmatrix} R_M \\ S_M \end{bmatrix} = F \begin{bmatrix} R_0 \\ S_0 \end{bmatrix}; \; F = F_M \cdot F_{M-1} \cdot \ldots \cdot F_i \cdot \ldots \cdot F_1 \tag{8}$$

The number of sections from this method depends on accuracy required, but $M \approx 100$ is sufficient for most apodized and chirped gratings[10]. M may not be arbitrarily large, because the coupling-mode-theory approximations are not valid when a uniform grating section is only a few gratings period, thus M must maintain the condition:

$$M << \frac{2n_{eff}L}{\lambda_D} \tag{9}$$

3. PARALLEL PROCESSING

The parallel processing is a strategy used in computing to get faster results for tasks that require a hard computational effort. These tasks can be processed in a serial form or divided in some parts as the follows:

- Small tasks are identified inside the complex task to be paralleled.
- Small tasks are distributed among some "workers", which will carry out them at the same time.
- The "workers" are coordinated.

To separate a complex program in subprograms to be executed simultaneously, basically it is possible to use two approaches of partitioning: functional and domain decompositions. In functional decomposition, the problem is divided in different tasks that will be distributed among processors to simultaneous running. This technique is ideal to a modular dynamic program, in which each task is a different program. In domain decomposition, the data are separated in groups that are distributed among some processors, which will simultaneously carry out the same program. The load balance must be maintained whatever the type of technique chosen. The distribution of the subroutines among the processors always must be made so that the running times of the subroutines are similar. If this observation is not considered, the performance of the parallel program will be inferior, because there are inactive processes waiting for parameters from other task to be executed.

As the processing is proportional to the number of individuals among the population, thus by implementing the subroutines with the same number of individuals one can make the parallel Genetic Algorithm and at the same time to guaranty load balancing among all processors. Obviously this rule is only valid if all processors have the same configurations.

The parallel processing was made with the MPI (Message Passing Interface) by using the version 1.2.4 of MPI LAM from Indiana University. The parallel processing strategy of genetic algorithm was based on domain decomposition, where the data were divided in groups and distributed among processors that carried out the same program simultaneously[13-14]. Taking to account that all computational effort is concentrated at evaluation of fitness function; this task was the chosen to be paralleled.

As can be seen at Fig. 2 the processing of GA is not totally carried out by slave computers. The task of master computer is executed without using parallel processing, only evaluating part of the population fitness, while the other part is divided and evaluated by the slave computers. Each slave evaluates the fitness of its subpopulation and sends to master process a table with those fitness values, while the others repeat this procedure too. Thus, the master process gets together the values tables at a single array, which is used by GA.

The cluster used to parallel processing consists of seven workstations (AMD Athlon 1800 MHz and 1.5 GB of RAM) and one workstation (AMD Athlon 1800 MHz with dual processors and 3.0 GB of RAM). As all the workstations have equal processors, thus by dividing the population in equivalent parts for each slave was implemented the load balancing.

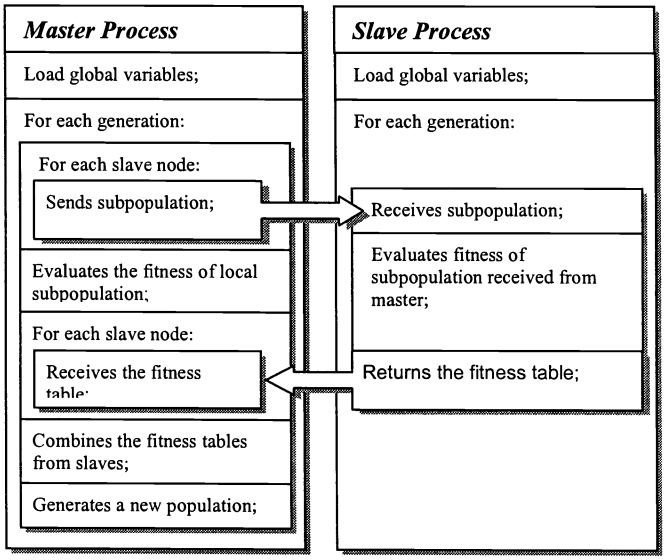

Fig. 2: Design of the parallel program for the configuration master-slave.

4. RESULTS

This work reports two designs of nonuniform gratings where are found the parameters of the gratings that operate at the spectral range of interest.

The first device to be optimized is a fiber Bragg grating, in which the target is r=1 at $1550.2 \leq \lambda \leq 1550.6$ nm and r=0 out of this region. 1000 equidistant wavelengths were used at (1). The length of the grating is L=1cm, the effective index is n_{eff}=1.45, the fringe visibility is v=1 and the design wavelength is λ_D = 1550 nm. The restrictions imposed are $10^{-5} \leq \Delta z_i \leq 10^{-3}$ and $0.0 \leq \delta n_{eff} \leq 4\times10^{-4}$. The reflectivity and the profile for δn_{eff} may be seen at Fig. 3 and 4, respectively. Fig. 5 shows group delay versus wavelength.

The second design is a grating with the same parameters of the first, but was added other restriction, in which the relative difference between successive sections must be up to 5%. The reflectivity, profile for δn_{eff} and delay may be seen at Fig. 6, 7 and 8.

Comparing Fig. 3 to Fig. 6 and Fig. 4 to Fig. 7, one can note that this restriction allows to find a smooth response and a less complex profile. According to literature, smooth variations give rise to better solutions[10], such as gratings with Gaussian profile.

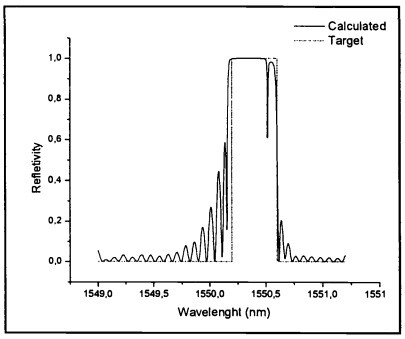

Fig. 3. Reflectivity calculated for a fiber Bragg grating with $6\times10^{-5} \le \Delta z_i \le 10^{-3}$ and $0.0 \le \delta_{neff} \le 4\times10^{-4}$ in a spectral region $1550.2 \le \lambda \le 1550.6$ nm.

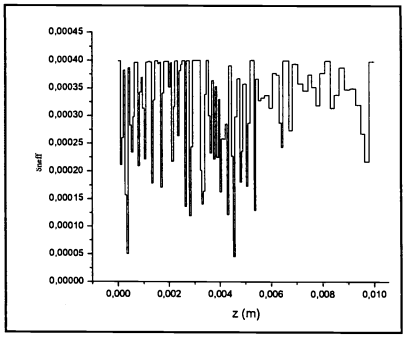

Fig. 4. Profile for δ_{neff} versus wavelength

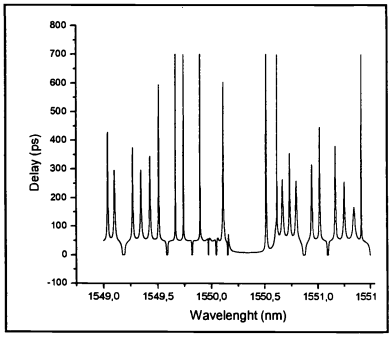

Fig. 5. Group delay versus wavelength

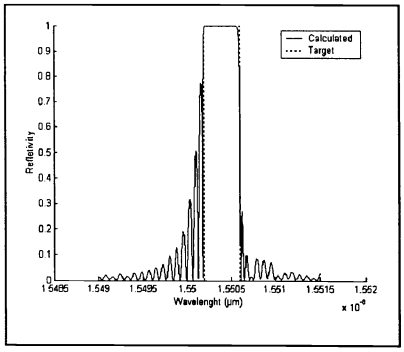

Fig. 6. Reflectivity calculated from a fiber Bragg grating with $0 \le \delta_{neff} \le 4\times10^{-4}$ in the spectral region $1550.2 \le \lambda \le 1550.6$ nm and with maximum relative difference for δn_{eff} of 5%.

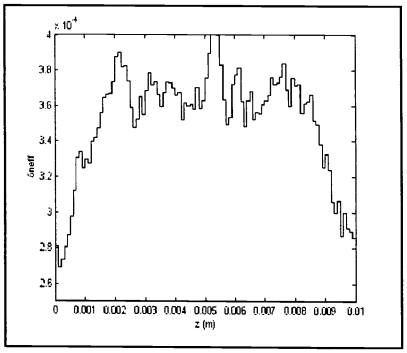

Fig. 7. Profile for δ_{neff} versus z .

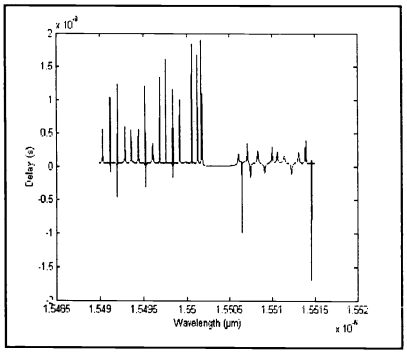

Fig. 8. Group delay versus wavelength

In order to analyze the effects of parallel processing at the two designs by using 1, 2, 4 and 8 processors, the processing time of each configuration can be seen at Table 1. Note the significant reducing of processing time when the number of processors is increased[14]. The computational performance can be analyzed by using a measurement named as speedup.

The speedup is the ratio between the processing time by using 1 processor and the parallel processing time. This value should be as close as possible the number of processors used. The closer to the number of processors the speedup is, the more efficient will be the parallel processing. The table 2 shows the speedup and the average efficiency for 1, 3, 4 and 8 processors.

At the Fig. 11 shows the speedup versus number of processors used. The proximity between the curve calculated and ideal curve emphasizes coarse-grain Parallelism. Coarse-grain Parallelism means that the total of computational operations is superior to communication operations, thus the coarse-grain Parallelism is, the more efficient the parallel processing is. Although communication operations occur with more frequency according to quantity of processors, this fact did not decreased the efficiency of parallel processing13. Table 2 shows this situation.

TABLE 1
PROCESSING TIME

	Average Time (s)	
Number of processors	Design 1	Design 2
1	121811	121710
3	41365	41365
4	31126	31082
8	15585	15614

TABLE 2
SPEEDUP AND EFFICIENCY OF PARALLEL PROCESSING

Number of processors	Average Speedup	Efficiency %
1	1	100
3	2.950172	98.33906586
4	3.914626	97.86564847
8	7.80542	97.56775229

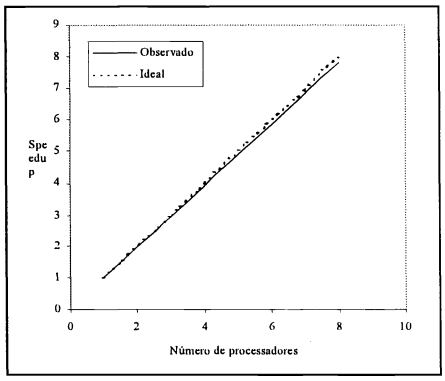

Fig. 11. *Speedup:* measured and ideal.

5. CONCLUSIONS

In this paper were presented two designs of Bragg gratings using parallel processing and genetic algorithm. The results shown that GA is a robust technique and feasible to be used in problems, which the search space is very complex. Although GA is a robust optimization method they suffer from high computational cost, but its use combined with parallel processing techniques shows that these restrictions can be solved improving the performance of this algorithm.

As the program works with solutions population it was simple to implement the load balancing at parallel program and was possible adapt it to the clusters with different configurations of processors. As the evaluation of fitness function is only part of GA with high computational cost, so dividing the serial program at this point to use the parallel processing was sufficient to get almost 100% of efficiency. The same parallel processing methodology used at this work can be used at others problems that present fitness function with high cost computational.

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