Wavelength Detection in FBG Sensor Network Using Tree Search DMS-PSO

J. J. Liang, P. N. Suganthan, C. C. Chan, and V. L. Huang

***Abstract*—As the number of fiber Bragg gratings (FBGs) increases, the conventional peak detection method will be unsuitable to detect Bragg wavelengths of FBG sensors in a wavelength-division-multiplexed (WDM) network. To solve this problem while achieving a higher accuracy at reduced computation cost, a novel tree search dynamic multiswarm particle swarm optimizer (TS-DMS-PSO) is developed. The TS-DMS-PSO yields better results with less computation cost based on the simulations (codes are available from the second author).**

***Index Terms*—Fiber Bragg grating (FBG), genetic algorithm, particle swarm optimizer, wavelength-division multiplexed (WDM).**

I. Introduction

A KEY issue in a wavelength-division-multiplexed (WDM) fiber Bragg grating (FBG) sensor network is the detection of the Bragg wavelength of each FBG in the network. A popular scheme for wavelength detection is the conventional peak detection (CPD) technique where a tunable optical filter is used to scan through the working range of the FBG spectrums to detect the peak (Bragg) wavelength of each FBG [1]. The CPD technique is not appropriate if spectrums of the FBGs in a network are overlapped [2]. The overlapping spectrums cause crosstalk between the sensors and introduce errors in Bragg wavelengths detected by the CPD method. This limits the performance in terms of the number of sensors and/or the measurement range of the sensors. By using an optimization algorithm, Bragg wavelength detection error and computation time are reduced while determining the Bragg wavelengths even when the spectrums of two FBGs in a network were overlapped. Due to the limitations of the optimization method, performance is unsatisfactory when the number of sensors is increased beyond two. This letter proposes a novel tree search dynamic multiswarm particle swarm optimizer (TS-DMS-PSO) with a periodically changing neighborhood and a tree structure to have enhanced global search ability resulting in a reduced computation time and increased accuracy for networks with a large number of FBGs. The principles of applying TS-DMS-PSO to solve this problem are presented in Section II. Simulation results and conclusions are in Sections III and IV, respectively.

II. Principles

A. Objective Function

The principles of using optimization technique to FBG sensor network may be explained as follows while referring

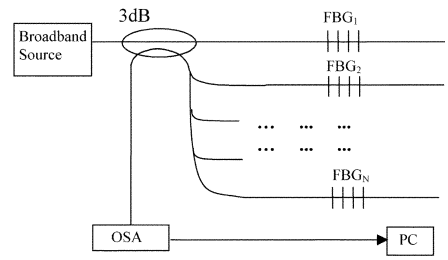

Fig. 1. Schematic diagram: PC: personal computer.

to the FBG network in Fig. 1. If $g_i(\lambda)\,(0 \leqslant g_i(\lambda) \leqslant 1; i = 1, 2, \ldots, N)$ are the spectral shapes of the N FBGs, the measured spectrum by using an optical spectrum analyzer (OSA) can be expressed as

$$R(\lambda) = \sum_{i=1}^{N} R_i g_i(\lambda - \lambda_{Bi}) + \mathrm{Noise}(\lambda) \tag{1}$$

where λ_{Bi}, R_i are the Bragg wavelength and peak reflectivity of the ith FBG. $\mathrm{Noise}(\lambda)$ is a random spectral fluctuation representing various noises. From the original reflection spectrums of the N FBGs, combined spectrum is constructed as follows:

$$R_v(\lambda, s) = \sum_{i=1}^{N} R_i g_i(\lambda - s_i), s = \{s_1, s_2, \ldots, s_N\}. \tag{2}$$

By varying s_i, diverse spectrums are constructed to cover all combinations of $R_i g_i(\lambda)$. The variance between the actual measured spectrum in (1) and the constructed spectrum in (2) [3] $g(s) = \int_0^\infty [R(\lambda) - R_v(\lambda, s)]^2 d\lambda, s = \{s_1, s_2, \ldots, s_N\}$ is minimized when $s_i = \lambda_{Bi}$. The s_i values yielding the smallest $g(s)$ are the Bragg wavelengths of FBGi $s = \{s_1, s_2, \ldots, s_N\}$. After discretization

$$g(s) = \sum_{j=1}^{L} [R(\lambda_j) - R_v(\lambda_j, s)]^2, s = \{s_1, s_2, \ldots, s_N\}. \tag{3}$$

By minimizing (3), high wavelength detection accuracy is achieved by "scanning" $s_i\,(i = 1, 2, \ldots, N)$. If the range is 1531.0 ~ 1532.0 nm and is sampled by 10 000 points, 0.1-pm accuracy is obtained. The number of calculation cycles of (3) by the conventional "scanning" method is 10 000 N. Hence, computation time that is too long makes it unsuitable in practice. A novel TS-PSO is developed to solve this special problem.

B. DMS-PSO

PSO is one of the evolutionary algorithms (EAs) [4]. In PSO, each solution is regarded as a particle with a fitness value and velocity. The particles fly in the N dimensional problem space by learning from the historical information of all the

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particles. The velocity of each particle is adjusted according to its personal best and the best performance achieved so far in its neighborhood. In DMS-PSO, the population is periodically and randomly divided into subswarms. Each swarm uses its own members to search for better solutions. Here, the solution space contains all sets of coefficients $s = \{s_1, s_2, \ldots, s_N\}$ that are possible solutions of (3). The DMS-PSO is summarized below.

Step 1) Initialize each particle randomly in the solution space with a position S_i and a velocity V_i. The position is a solution to (3). The current position is set as the particle's best position $p\mathrm{best}_i$. Each particle is evaluated by (3) as the objective. The best position of the kth swarm is denoted as $l\mathrm{best}_k$.

Step 2) Update the particles' velocities and positions

$$\begin{aligned}\boldsymbol{V}_i^{\mathrm{new}} &= w^* \boldsymbol{V}_{\boldsymbol{i}}^{\mathrm{old}} + c_1^* \mathbf{rand1}_i^* (p\mathrm{best}_{\boldsymbol{i}} - \boldsymbol{S}_{\boldsymbol{i}}^{\mathrm{old}}) \\ &\quad + c_2^* \mathbf{rand2}_{\boldsymbol{i}}^* (l\mathbf{best}_{\boldsymbol{k}} - \boldsymbol{S}_{\boldsymbol{i}}^{\mathrm{old}}) \\ \boldsymbol{S}_i^{\mathrm{new}} &= \boldsymbol{S}_i^{\mathrm{old}} + \boldsymbol{V}_i^{\mathbf{new}}\end{aligned}$$

where the ith particle belongs to swarm k. $\boldsymbol{S}_i$ and $\boldsymbol{V}_i$ are the position and velocity of particle $\boldsymbol{i}$. $\mathbf{rand1}_i = [\mathrm{rand1}_i^1, \mathrm{rand1}_i^2, \ldots, \mathrm{rand1}_i^N] \mathrm{rand2}_i = [\mathrm{rand2}_i^1, \mathrm{rand2}_i^2, \ldots, \mathrm{rand2}_i^N]$. $\mathrm{rand1}_i^j$ and $\mathrm{rand2}_i^j$ are uniformly distributed random numbers in $[0, 1]$. w is the inertia weight balancing the global and local search abilities where $w = 0.729$. $c_1 = c_2 = 1.49$.

Step 3) Evaluate each particle's new positions (solutions) using (3): $E_i^{\mathrm{new}} = g(S_i^{\mathbf{new}})$. Update $p\mathbf{best}_i$ as follows: if $g(p\mathbf{best}_i) \geqslant g(\boldsymbol{S}_i^{\mathbf{new}}), p\mathbf{best}_i = \boldsymbol{S}_i^{\mathrm{new}}$. Update $l\mathbf{best}_{\boldsymbol{k}}$ as follows: if $g(l\mathbf{best}_{\boldsymbol{k}}) \geqslant g(\boldsymbol{S}_i^{\mathbf{new}})$ & particle $i \in$ swarm k, $l\mathbf{best}_{\boldsymbol{k}} = \boldsymbol{S}_i^{\mathbf{new}}$.

Step 4) Every R generations, regroup the particles randomly to let the particles have new neighbors.

Step 5) Stop the search with the best solution found as the result, if no better solution is found for many generations or the maximum fitness evaluations (Max_FEs) is completed. Otherwise, go to Step 2.

C. TS-DMS-PSO

The fitness evaluated using (3) has a computation complexity of $O(L)$, where L is the number of sample points. If the span width of the OSA is 1 nm, the number of sample points needed for the accuracies of 1 and 0.1 pm are 1000 and 10 000, respectively. Thus, the TS method is proposed to search the large search space with less time-consuming low accuracy fitness function to obtain an initial solution, and then shrink the search range with the obtained initial solution as the center and use a higher accuracy fitness function to refine the result. The original DMS-PSO is extended to TS-DMS-PSO. For M-layers TS-DMS-PSO, (3) is divided into M subobjectives. In the subobjective of each layer, a different L value is used. In each layer, DMS-PSO is used to search for the optimal solution to the corresponding subobjective. Equation (3) becomes

$$g(\boldsymbol{s}, \boldsymbol{L_m}) = \sum_{j=1}^{L_m} [R(\lambda_j) - R_v(\lambda_j, s)]^2 \boldsymbol{s} = \{s_1, s_2, \ldots, s_N\} \quad (4)$$

where $m = 1, 2, \ldots, M$ and $L_1 < L_2 < \cdots < L_M$.

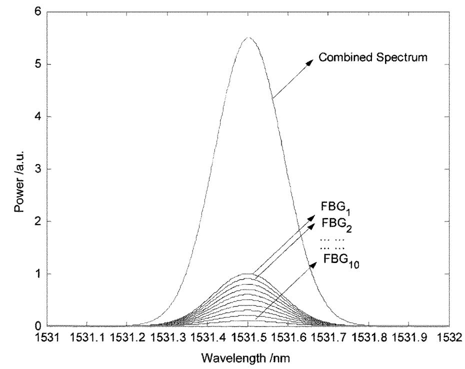

Fig. 2. Uncontaminated spectrums of the 10-FBGs sensor network from the OSA when λ_{B10} and ξ are 1531.50 nm and 0.1 pm, respectively.

If the original search range for the problem for layer i is $[\boldsymbol{S}_i^{\min}, \boldsymbol{S}_i^{\max}]$ and the coarse result achieved for layer i is S_i, the new ensued search range for layer $i+1$ is $[\max(\boldsymbol{S}_i^{\min}, \boldsymbol{S}_i - (\boldsymbol{S}_i^{\max} - \boldsymbol{S}_i^{\min})/10), \min(\boldsymbol{S}_i^{\max}, \boldsymbol{S}_i + (\boldsymbol{S}_i^{\max} - \boldsymbol{S}_i^{\min})/10)]$.

III. Simulation Results

The schematic of a WDM N-FBG sensor network is in Fig. 1. Light from a broadband source is coupled from one arm of a $2 \times N$ optical fiber coupler with a coupling ratio of $1/N$ to the WDM N-FBG sensor network. The reflectivities (R_i) and the Bragg wavelengths (λ_{Bi}) are both different for all FBGs, $i = 1, 2, \ldots, N$. The reflected light from all FBGs is coupled back into the other arm of the same coupler and the combined spectrum is detected by an OSA where the span width of the OSA covers the whole spectral ranges of all FBGs. The OSA samples the spectrum at L points and passes the samples to a PC.

The spectrums of the FBGs are Gaussian shaped [6] and their full-width at half-maximum (FWHM) are $\Delta\lambda$. The peak reflectivities and/or the shapes of the FBGs in the WDM network should be different, so the reflectivity of the ith FBG in the WDM N-FBGs sensor network is set to be $(i \times R_N)/N$ and the separation of the Bragg wavelengths between the adjacent FBGs $(\lambda_{Bi} - \lambda_{B(i-1)})$ is ξ pm $(2 \leqslant i \leqslant N)$. The FWHMs of all FBGs are assumed to be 0.2 nm. The span width of OSA is set to be 1 nm (1531.0–1532.0 nm) and is sampled by 10 000 points. Hence, resolution is 0.1 pm. Individual and combined uncontaminated spectrums of the 10-FBG sensor network from the OSA is in Fig. 2.

The simulation is conducted with a different number of sensors and signal-to-noise ratios (SNRs). For each pair of FBGs and SNR, the simulation is repeated 20 times. We used the simple GA, DMS-PSO, and TS-DMS-PSO. The population size is 30. The maximum number of fitness evaluations (Max_FEs) is 60 000. The algorithms are terminated when the best result did not improve for 200 generations or Max_FEs is completed. Other parameters are $-$GA: 14 bits per coefficient, crossover probability $Pc = 1$, mutation probability $Pm = 0.1$; DMS-PSO: ten subswarms, $R = 10$; TS-DMS-PSO: 10 subswarms, $R = 10, M = 2, L_1 = 1000, L_2 = 10\,000$.

The mean values of the root-mean-square (rms) values of the Bragg wavelength detection errors of the 20 runs are used to evaluate the algorithms. A P4 3G, 1024 MB PC is used in this simulation. The results and the computation costs are compared in Fig. 3. From the results, we observe that DMS-PSO

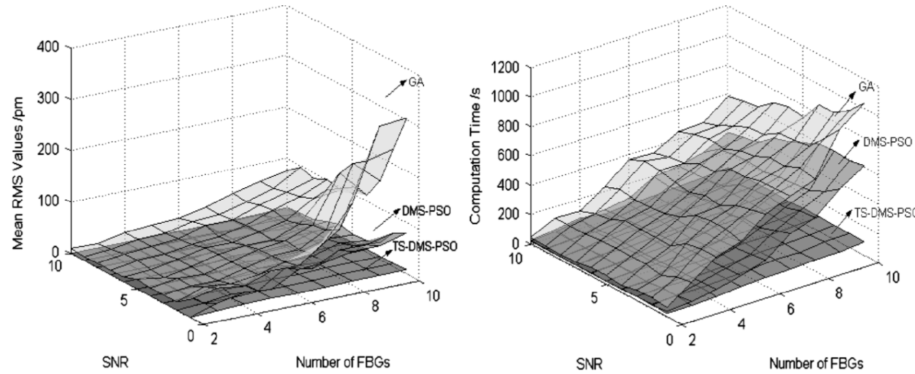

Fig. 3. Mean rms detection errors and computation costs for partially overlapped case ($\xi = 0.1$ pm).

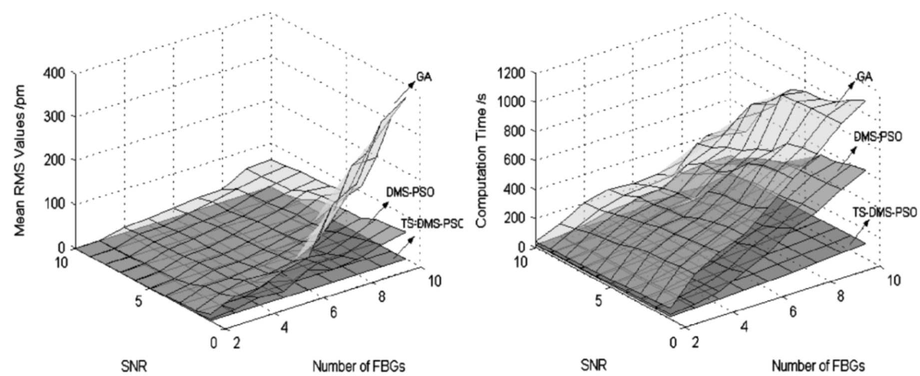

Fig. 4. Mean rms detection errors and computation costs for overlapped case ($\xi = 0.0$ pm).

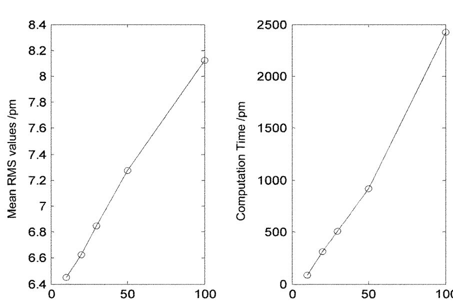

Fig. 5. Mean errors and computation for partially overlapped case ($\xi = 0.1$ pm).

and TS-DMS-PSO presents smaller errors than the simple GA. TS-DMS-PSO performs better when the number of FBGs and the noise level increase. If the number of sensors is equal to ten and SNR is one, the mean rms values of the wavelength detection error for the 20 runs achieved by the simple GA, DMS-PSO, and TS-DMS-PSO are 301.82, 78.69, and 8.01 pm, respectively. However, TS-DMS-PSO requires the lowest computation time of 84.584 compared to 1026.8 and 601.69 s.

To test the algorithms when the sensors are completely overlapped, ξ is set to 0.0 pm. The results of 20 runs are plotted in Fig. 4. When SNR is one, for ten FBGs, the mean rms values of the wavelength detection error achieved by the GA, DMS-PSO, and TS-DMS-PSO are 370.18, 61.67, and 0.00 pm, respectively. The computation times are 1079.9, 601.32, and 97.516 s.

Simulations on two to ten FBGs have shown TS-DMS-PSO yielding the best results at the lowest computation cost when the sensors are partially or completely overlapped. To further evaluate the performance of TS-DMS-PSO, simulations are conducted on 10, 20, 30, 50, and 100 FBGs when SNR $= 10$ for the partially overlapped case and the results are shown in Fig. 5. TS-DMS-PSO still achieves acceptable results within the given Max_FEs. But with the FBGs increasing, it becomes more and more time consuming because of the fitness evaluations.

IV. Conclusion

A novel TS-DMS-PSO has been developed for a WDM FBG sensor network for the detection of Bragg wavelengths of the sensors. Simulations show that TS-DMS-PSO can accurately determine the Bragg wavelengths of the sensors, when the spectrums of the FBGs are partially or completely overlapped. With two layers, TS-DMS-PSO consumes only 10%–20% computation time and achieves better results than GA and the original DMS-PSO. For a 100-FBG network, the mean rms value of errors achieved by TS-DMS-PSO is 8.12 pm when SNR $= 10$.

References

[1] E. Udd, *Fiber Optic Smart Structure*. New York: Wiley, 1995.
[2] C. Z. Shi, C. C. Chan, W. Jin, Y. B. Liao, Y. Zhou, and M. S. Demokan, "Improving the performance of a FBG sensor network using a genetic algorithm," *Sens. Actuators A*, vol. 107, pp. 57–61, 2003.
[3] J. M. Gong, J. M. K. MacAlphine, C. C. Chan, W. Jin, M. Zhang, and Y. B. Liao, "A novel wavelength detection technique for fiber Bragg grating sensors," *IEEE Photon. Technol. Lett.*, vol. 14, no. 5, pp. 678–680, May 2002.
[4] P. N. Suganthan, "Particle swarm optimization with a neighborhood operator," in *Proc. CEC*, vol. 3, Washington, DC, 1999, p. 1958.
[5] J. J. Liang and P. N. Suganthan, "Dynamic multi-swarm particle swarm optimizer," in *P. Proc. IEEE Swarm Intel. Symp.*, 2005, pp. 124–129.
[6] M. G. Xu, H. Geiger, and J. P. Dakin, "Modeling and performance analysis of a fiber Bragg grating interrogation system using an acousto-optic tunable filter," *J. Lightw. Technol.*, vol. 14, no. 3, pp. 391–396, Mar. 1996.