Improving the performance of a FBG sensor network using a novel dynamic multi-swarm particle swarm optimizer

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A novel evolutionary algorithm called dynamic multi-swarm particle swarm optimizer (DMS-PSO) is used to detect Bragg wavelengths of fiber Bragg grating (FBG) sensors in a wavelength division multiplexed (WDM) network. Simulation and experimental results show that DMS-PSO achieves higher accuracy with less computation cost compared to the conventional peak detection approach and the simple binary genetic algorithm when the sensors are partially or completely overlapped in noisy environment.

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Keywords: Fiber Bragg Grating (FBG), FBG sensor network, Wavelength division multiplexed (WDM), Particle Swarm Optimization, Evolutionary Algorithm

1. Introduction

A key issue in wavelength division multiplexed (WDM) fiber Bragg grating (FBG) sensor network is the accurate detection of the Bragg wavelength of each FBG within the network. A popular scheme for wavelength detection is the so-called conventional peak detection (CPD) technique where a tunable optical filter (TOF) is used to scan through the working range of the FBG spectrums and detect the peak (Bragg) wavelength corresponding to each FBG [1]. The CPD technique is however not much applicable when the spectrums of the FBGs within the network are partially or fully overlapped 0. The overlapping spectrums would cause crosstalk among the sensors and then introduce errors in Bragg wavelength detections. This limits the system performance in terms of either the number of sensors or the measurement range of the sensors within the network.

Optimization techniques are needed to solve this kind of problem. Considering this is a complex multimodal problem, the classic gradient search method cannot determine good results. Evolutionary algorithm (EA) is a good choice as it has the ability to solve complex nonlinear optimization problems. By the use of EA, the Bragg wavelength detection error and the computational time could be reduced. A binary Genetic Algorithm (GA) has been used for the determination of the Bragg wavelengths [2] and the results showed that this technique was capable of quickly determining the Bragg wavelengths even when the spectrums of the FBGs within the network were partially or completely overlapped. However, because of the limitations of the simple binary GA, the performance could not be improved further when the number of sensors is increased. In this paper, a novel dynamic multi-swarm particle swarm optimizer (DMS-PSO), which has better global search ability, is employed instead of the simple binary GA in order to improve the performance for more FBGs network and reduce the computational time. The basic principle of applying DMS-PSO technique to the WDM FBG sensor network is given in Section 2. The numerical simulation results and experiments are shown in Section 3 and 4, respectively. The conclusion is given in Section 5.

2. Principles

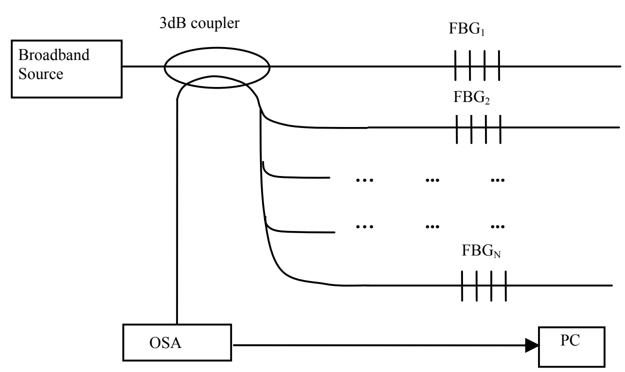


Fig. 1. Schematic diagram for N-FBG network; OSA: optical spectrum analyzer; FBG: fiber Bragg grating; PC: personal computer.

The basic principles of applying the EA technique to FBG sensor network may be explained as follows referring to the FBG network as shown in Fig. 1.

Assume that $g_i(\lambda)$ ($0 \le g_i(\lambda) \le 1; i = 1, 2, ..., N$) are the spectral shapes of the N FBGs. The measured spectrum from say an optical spectrum analyzer (OSA) may be expressed as

$$R(\lambda) = \sum_{i=1}^{N} R_{i0} g_i(\lambda - \lambda_{Bi}) + Noise(\lambda) \quad (1)$$

where λ_{Bi} , R_i are the Bragg wavelength and peak reflectivity of the i^{th} FBG. $Noise(\lambda)$ is a random spectral fluctuation accounting for various noises occurring in the system. From the original reflection spectrums of these N FBGs, combined spectrum can be constructed as follows

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

By varying s_i , variable spectrums are constructed that cover all possible combinations of $R_i g_i(\lambda)$. The variance between actual measured spectrum given in Eq. (1) and the artificially constructed spectrum given in Eq. (2) [3]

$$g(\mathbf{s}) = \int_0^{\infty} [R(\lambda) - R_v(\lambda, \mathbf{s})]^2 d\lambda \, , \quad \mathbf{s} = \{s_1, s_2, ..., s_N\} \quad (3)$$

is minimized when $s_i = \lambda_{Bi}$. The values of s_i corresponding to the minimum variance are therefore respectively the Bragg wavelengths of FBG_i. Hence, this is a minimization problem:

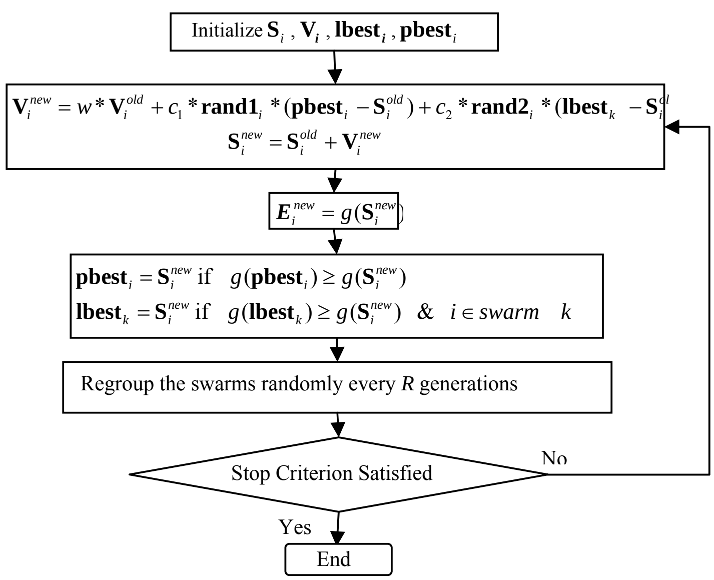
$$\text{Min} \ \{g(\mathbf{s})\} = \int_0^{\infty} [R(\lambda) - R_v(\lambda, \mathbf{s})]^2 d\lambda \, , \quad \mathbf{s} = \{s_1, s_2, ..., s_N\} \quad (4)$$

After discretization, it becomes

$$\text{Min} \ \{g(\mathbf{s})\} = \sum_{j=1}^{L} [R(\lambda_j) - R_v(\lambda_j, \mathbf{s})]^2 \, , \qquad \mathbf{s} = \{s_1, s_2, ..., s_N\} \quad (5)$$

This is an optimization problem and the objective is to find the best solution $\boldsymbol{s}$ to minimize $g(\mathbf{s})$. Based on the aforementioned principle, wavelength detection accuracy of a few picometers can be achieved by 'scanning' s_i ($i = 1, 2, ..., N$) within specified range at sufficiently fine steps. If the range is set to 1531.0 nm ~ 1532.0 nm and is sampled in 1000 points, the accuracy of 1pm is obtained and the number of calculation cycles of Eq. (5) by conventional 'scanning' method is 1000^N, so that the computational time is very long and makes it difficult to be applied in some practical situations. This minimization problem is a complex multimodal problem that can potentially trap gradient descent type search algorithms in a local optimum. As EA has good global search ability, we employ an EA to solve this minimization problem.

Particle swarm optimizer (PSO) which is introduced in 1995 [4-5] is a new member in the evolutionary computation field. It emulates flocking behavior of birds to solve the optimization problems and it is easy to use and converges fast. Since it is introduced, it has shown its powerful search ability in various application areas. In PSO, each solution is regarded as a particle. All particles have their own fitness values and velocities. In the local version of PSO, the whole population is regarded as a swarm, and the swarm is divided into sub-swarms according to different structure topologies. Each particle has **pbest** (personal best), the best position (solution) found so far by the particle itself and **lbest** (local best), the best position (solution) has been found so far by the sub-swarm the particle belongs to. The particles fly through the N dimensional problem space by learning from the historical information of all the particles. And in this way, better and better positions (solutions) are found in the search process. DMS-PSO is developed based on the basic PSO and has demonstrated good performance on complex multimodal problems [6].



m: Each swarm's population size k: Swarms' number R: Regrouping period
Stop criterion: 1. get the max fitness evaluation times (Max_FEs)
2. the best solution found so far is not improved for a certain generation

Fig. 2. DMS-PSO's flowchart.

The process of DMS-PSO is shown in Fig. 2. The solution space contains all sets of coefficients $\mathbf{s} = \{s_1, s_2, ..., s_N\}$ that are possible solutions of (5). When applying DMS-PSO to (5), first the swarm number and the particle number in each swarm are set. For example, if 10 sub-swarms are used and each sub-swarm has 3 particles, there are 30 particles in total performing the search process.

Step 1: Initialization: Initialize these particles randomly in the solution space; each particle has a position $\mathbf{S}_i$ and a velocity $\mathbf{V}_i$. The position is just the corresponding solution in Eq. (5). The current position is set as the particle's historical best position $\mathbf{pbest}_i$. Each particle is evaluated by using Eq. (5) as the objective function. The best position found by the k^{th} swarm is represented as $\mathbf{lbest}_k$.

Step 2: Update the particles' velocities and positions (solutions) as below:

$$\mathbf{V}_i^{new} = w * \mathbf{V}_i^{old} + c_1 * \mathbf{rand1}_i * (\mathbf{pbest}_i - \mathbf{S}_i^{old}) + c_2 * \mathbf{rand2}_i * (\mathbf{lbest}_k - \mathbf{S}_i^{old}) \quad (6)$$

$$\mathbf{S}_i^{new} = \mathbf{S}_i^{old} + \mathbf{V}_i^{new} \quad (7)$$

where the i^{th} particle belongs to sub-swarm k. $\mathbf{S}_i$ is the position of the i^{th} particle and $\mathbf{V}_i$ represents the rate of the position change (velocity) for particle i. $c_1 = c_2 = 1.49$, $\mathbf{rand1}_i = [rand1_i^1, rand1_i^2, ..., rand1_i^N]$ and $\mathbf{rand2}_i = [rand2_i^1, rand2_i^2, ..., rand2_i^N]$, $rand1_i^j$ and $rand2_i^j$ are uniform distributed random numbers in the range [0,1]. w is the inertia weight used to balance between the global and local search abilities and w =0.729.

Step 3: Evaluate each particle's new positions (solutions) using Eq. (5).

$$E_i^{new} = g(\mathbf{S}_i^{new}) \quad (8)$$

Update $\mathbf{lbest}_k$ and $\mathbf{pbest}_i$ as follow:

If $g(\mathbf{pbest}_i) \geq g(\mathbf{S}_i^{new})$,

$$\mathbf{pbest}_i = \mathbf{S}_i^{new} \quad (9)$$

If $g(\mathbf{lbest}_k) \geq g(\mathbf{S}_i^{new})$ & particle $i \in swarm \quad k$,

$$\mathbf{lbest}_k = \mathbf{S}_i^{new} \quad (10)$$

In this way, $\mathbf{lbest}_k$ and $\mathbf{pbest}_i$ are always the best solutions found so far by the sub-swarm k and particle i respectively.

Step 4: Every R generations, regroup the particles randomly to let the particles have new neighbors. Here R is called regrouping period. In another word, the swarm is divided into sub-swarms randomly every R generations.

Step 5: Stop the optimization with the best solution found as the optimized result, if no better solution has been found for a certain number of generations (e.g. 200 generations) or the maximum number of fitness evaluations (Max_FEs) is completed. Otherwise, go to Step 2.

3. Simulation results

The schematic diagram of a WDM *N*-FBGs sensor network used in the following simulations is shown in Fig. 1. Light from a broadband source (BBS) is coupled from one arm of a $2 \times N$ optical fiber coupler with a coupling ratio of $1/N$ to a WDM *N*-FBGs sensor network. The reflectivities (R_i) and the Bragg wavelengths (λ_{Bi}) are both different for all FBGs where subscript $i=1,2,\ldots N$. 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 optical spectrum analyzer (OSA) where the span width of the OSA covers the whole spectral ranges of all FBGs. The OSA samples the spectrum into k points and passes the sampled data to a personal computer (PC) for further analysis.

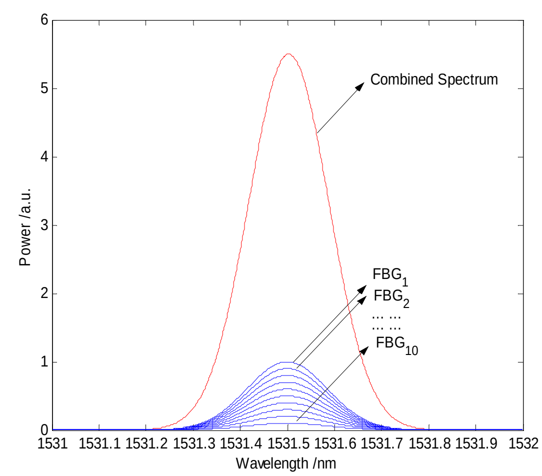


Fig. 3. The spectrums of the 10-FBGs sensor network from the OSA when λ_{B10} and ξ are 1531.50 nm and 1 pm respectively.

Assume the spectrums of the FBGs are Gaussian shape 0 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 i^{th} 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 $(2 \leq i \leq N)$. For example, in a 10-FBGs sensor network, the reflectivity of the FBG (R_i) is $(i \times R_{10})/10$ where R_{10} is equal to 100%. The Bragg wavelength of the FBG (λ_{Bi}) is $\lambda_{B10} - \xi \times (10 - i)$ where λ_{B10} and ξ are 1531.50 nm and 1 pm respectively. Moreover, the FWHM of all FBGs are assumed to be 0.2 nm. The span width of the OSA is set to be 1 nm (1531.0 nm-1532.0 nm) and is sampled by 1000 points. The individual and combined uncontaminated spectrum of the 10-FBGs sensor network from the OSA is shown in Fig. 3. The detection for each Bragg wavelength is nearly impossible when the 10 FBGs are partially overlapped. Therefore, the DMS-PSO algorithm is used to detect for each Bragg wavelength on this partially overlapping case.

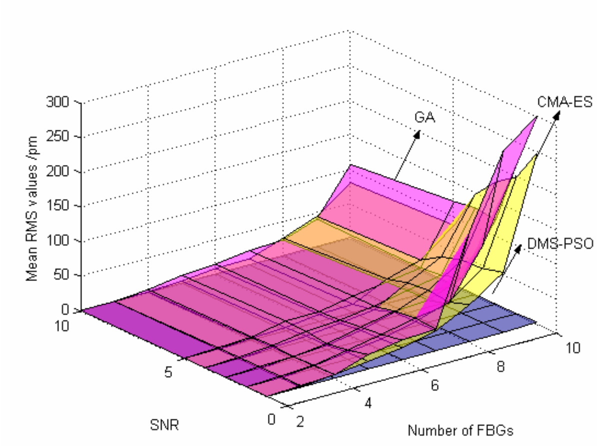


Fig. 4. The mean RMS values of the wavelength detection error due to by GA CMA-ES and DMS-PSO.

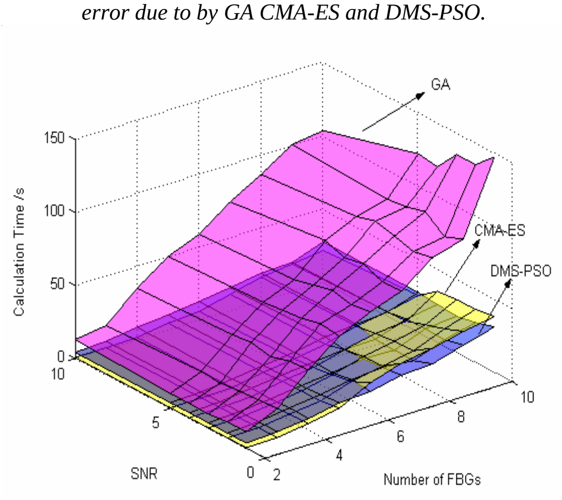


Fig. 5. Comparison of the Computational Cost of GA, CMA-ES and DMS-PSO.

In addition to the simple binary GA, one of the best EAs known as the covariance matrix adapted evolution strategy (CMA-ES) is also tested in the simulation with DMS-PSO. The simulation is conducted with different number of sensors and with different signal-to-noise ratio (SNR) conditions. The white noise is added to each FBG for testing the ability of the EAs to detect the Bragg wavelength in a noisy environment. For each specified number of FBGs and SNR, the simulation is repeated for 10 times. The Bragg wavelength detection for each case is accomplished by using the binary GA, CMA-ES and DMS-PSO algorithms. For all three algorithms, the maximum number of fitness evaluations (Max_FEs) is set to 50,000. The parameters of the GA [7] are: population size 100, the number of bits per coefficient 10, crossover possibility Pc =1, mutation possibility Pm = 0.1. The default parameters are used in CMA-ES. For DMS-PSO, population size is 30 and the regrouping period R is 10. The algorithms will be terminated when the best result, which is achieved so far, has not been improved within 200 generations. The mean values of the root-mean-square (RMS) values of the Bragg wavelength detection errors of the 10 runs are used to evaluate the performance of algorithms. A P4 3G, 1024MB personal computer is used in this simulation. The results are plotted in Fig. 4 and the computational cost of GA and DMS-PSO are compared in Fig. 5. Here the computational cost is the cost we spent to get the final solution and the computation time is employed to reflect the computational cost.

From the results, DMS-PSO achieves the zero error for all cases except for 10 FBGs with SNR at 1 while the simple GA and CMS-ES only achieve zero error for two sensors case. For 10 sensors with SNR at 1, the mean of RMS values of the wavelength detection error for the DMS-PSO is 1.60 pm, while the mean error of the GA and CMS-ES are 298.77 pm and 245.35 pm respectively. Moreover, the computational cost of the DMS-PSO is comparable to the CMS-ES and is about 5~10 times lower than that of the binary GA. For 10 FBGs case, when SNR is equal to 1, the computation times are 146.24s, 37.21s and 30.11s for GA, CMA-ES and DMS-PSO respectively. Additionally, Quasi-Newton method is also tested under the same condition for 10 sensors with SNR at 1, the mean of RMS values of the wavelength detection error for Quasi-Newton method is 871.24 pm. Comparatively, evolutionary algorithms achieved much better results than the gradient search method and the DMS-PSO performs better with less number of fitness evaluations than the other two algorithms [8-11].

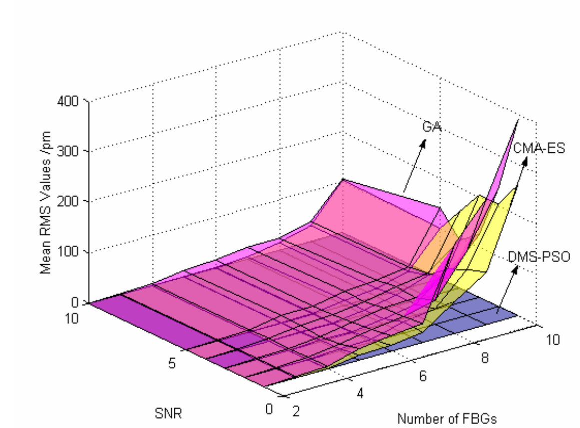


Fig. 6. The mean RMS values of the wavelength detection error due to the simple GA, CMA-ES and DMS-PSO for overlapping situation (Accuracy: 1pm).

In order to test the algorithms' performance in the overlapped situation, ξ is set to be 0 pm and then repeat the simulation. The results are presented in Fig. 6. Except that the mean RMS values are 0.80 pm and 0.20 pm for 10 FBGs case when SNRs are equal to 1 and 2 respectively, zero errors are achieved by DMS-PSO for the other cases. The results of the simple GA and CMA-ES are much worse. From the results shown in Fig.4 and 6, it is observed that irrespective of partial overlapped or totally overlapped, DMS-PSO performs well even with a large number of FBGs in the WDM network.

4. Experimental results

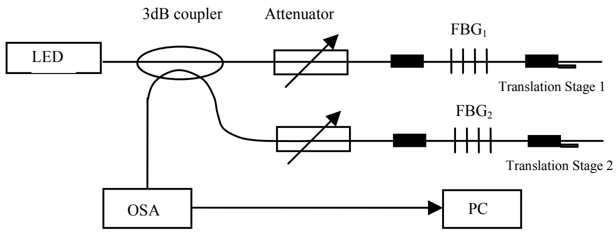


Fig. 7. Experimental setup for two FBGs LED: light emitting diode; OSA: optical spectrum analyzer; FBG: fiber Bragg grating; PC: personal computer.

Experiments are conducted using a setup shown in Fig. 7. Light from an LED illuminates two FBGs via a 50/50 coupler, and an OSA was used for spectral analysis and was connected to a computer for further signal processing. The span width of the OSA was set to 2 nm, and sampled by 1000 points; the corresponding sample resolution is 2 pm. The two FBGs approximately have the same spectral shape with a 3 dB full-width of about 0.2 nm. The peak reflectivity of FBG_1 was made 3 dB lower than that of FBG_2 through the use of a variable attenuator. Before starting the experiments, the reflection spectra of the two FBGs were measured using the OSA and used to construct the variable spectrum.

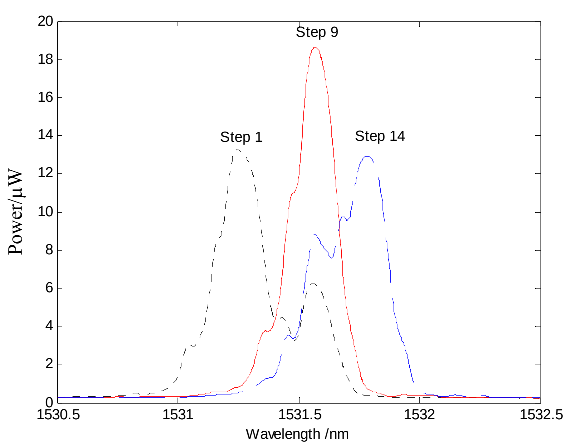


Fig. 8. Spectra measured from OSA for different applied strain values (one step corresponds to 33 με).

During the experiments, an arbitrary but fixed strain was firstly applied to FBG_1 through the use of translation stage #1. The Bragg wavelength of FBG_2 was firstly shifted to approximately 1531.2 nm through translation stage #2. The applied strain was then increased at steps of 33 με with an accuracy of ~3 με . Fig.8 shows the spectrums measured by OSA for some typical applied strain values corresponding to steps 1, 9 and 14. It can be seen that the two peaks merged partially (step 1 and 14) or fully (step 9), and the detection of the Bragg wavelengths of the two FBGs.

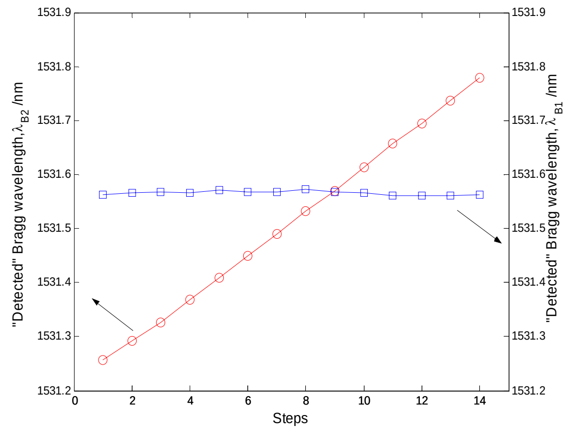


Fig. 9. Measured Bragg wavelength vs. applied strain (one step corresponds to 33 με).

For each applied strain value, DMS-PSO and the simple GA and CMA-ES were used to calculate the Bragg wavelength of two FBGs according to Eq. (5). For DMS-PSO, the population size is set to 30, the max fitness evaluation times (Max_FEs) is set to 6,000 and the regrouping period *R* is set to 10. The time taken for each calculation was about 2s, when a P4 3G, 1024MB Computer was used. Fig. 9 shows the calculated Bragg wavelengths obtained by DMS-PSO when the strain applied to FBG_2 was changed from 30 to 460 με and fixed strain was applied to FBG_1. The detection accuracies in term of standard deviation about the best-fit line over the whole operation range of 430 με , were found to be 1.60 pm and 1.68 pm for FBG_1 and FBG_2, respectively. The simple GA was also able to solve this problem by taking two times the computation time of the DMS-PSO and the CMS-ES can achieve the problem with comparable time. This is consistent with the simulation results presented in Section 3.

5. Conclusions

A novel evolutionary algorithm called dynamic multi-swarm particle swarm optimizer (DMS-PSO) has been applied to a WDM FBG sensor network to detect the Bragg wavelengths. Simulations and experiment have shown that the DMS-PSO can quickly and accurately determine the Bragg wavelengths of the sensors, when the spectrums of the FBGs with the network are partially or completely overlapped. When the number of sensors is 10 and SNR is equal to 1, the mean RMS values of the wavelength detection error achieved by DMS-PSO for 10 runs is 1.60 pm and 0.80 pm for partially or completely overlapped cases respectively in the simulation. In the experiment, when one sensor was shifted and another is fixed, the detection accuracies for the two sensors were 1.60 pm and 1.68 pm. The limitation of the CPD technique is overcome. The comparisons between GA, CMA-ES and DMS-PSO demonstrate a better search ability with higher accuracy and less computation cost of the DMS-PSO. In addition, DMS-PSO is also easy to use, does not have many parameters to be adjusted and requires less memory.

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