A real-coded genetic algorithm for distributed fiber Bragg grating sensor

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A real-coded genetic algorithm (RGA) for fiber Bragg grating (FBG) distributed sensing is presented. The distributed strain fields along the fiber Bragg grating sensor (FBGS) are real coded into genes, and the concept of elitism and simulated annealing are also included in this algorithm. Compared with the binary coded genetic algorithm, this method is more simple and efficient. Only with the reflect spectrum of distributed FBGS, the strain fields distribution can be exactly demodulated even in the regions with significant strain gradients. The algorithm is a promising method for demodulating the distributed FBGS, which can be used for structural failure analysis and structural damage identification.

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From the earliest stage of their development, fiber Bragg gratings (FBGs) have been considered excellent sensor elements, suitable for measuring static and dynamic fields, such as temperature, strain, and pressure[1]. For quasi-distributed strain sensing, the fiber Bragg grating sensor (FBGS) is regarded as a point sensor and the strain distribution along the FBGS is averaged along the fiber axis. But in some situation, such as local damage identifying within a material system, it is important to derive the strain distribution along fiber axis as to locate the regions where strong strain non-uniformities occur. The reflect spectrum of FBGS can be easily measured with a conventional optical spectrum analyzer (OSA). When the reflect spectrum of FBGS is derived, we can reconstruct the period distribution which has a linear relation with the strain distribution along the fiber axis. The simplest technique is the intensity spectrum based approach (ISB) method[2], but it is only valid for monotonically varying strain fields and not suitable for strain fields with great gradient. Other reconstruct algorithms such as the Fourier transform technique[3], the iterative Gel'fand-Levitan-Marchenko method[4], the time-frequency signal representations[5] and the Layer peeling techniques[6], but all these methods needs all the information (including phase information) of the reflect spectrum of FBGS, which limits their use in distributed strain sensing. Recently some heuristic approaches have been developed for the solution of the FBG inverse problem[7,8]. Skaar *et al.*[7] proposed a fiber grating synthesis method based on genetic algorithm that is binary coded and with low running speed. Here we present a new real-coded genetic algorithm (RGA) with high running speed that is suitable for FBG distributed strain sensing.

The algorithm is started with a set of solutions (strain distributions, represented by chromosomes) called population. The strain distributions along the fiber axis are divided to M segments and coded as genes of chromosomes. Within each segment, the strain distribution is regarded as a const. By increasing the segment number M, the strain distribution along the FBGS can be approximated well. Then RGA algorithm is used to reconstruct the strain distribution along fiber axis with the reflect spectrum of FBGS.

The procedure of our RGA algorithm is summarized as follows.

Step 1: Get the reflect spectrum of FBGS. (Here we simulate the spectrum of FBGS using the well-known transfer matrix method[9] just for illustration, in practical situation, it can be derived from OSA.)

Step 2: Generate random population of M chromosomes whose genes are represented by strains, and the genes are in the predefined strain range:

$$\varepsilon_i \in [A, B] \quad (i = 1, \cdots, M), \tag{1}$$

where A and B are the lower bound and upper bound of strain. And the strain induced non-uniform period Λ_i distribution is

$$\Lambda_i = \Lambda_0 \left[1 + (1 - p_e)\,\varepsilon_i\right], \tag{2}$$

where Λ_0 is the grating period without strain, $p_e \approx 0.26$ is the strain-period relation coefficient of FBGS.

Step 3: Evaluate the fitness of each chromosome in the population and return the best solution in current population. If the end condition is satisfied, terminate the algorithm. The fitness formulation is chosen as

$$F = \frac{1}{\sum_m \left|R_{\mathrm{calc}}(\lambda_m) - R_{\mathrm{targ}}(\lambda_m)\right|^2}, \tag{3}$$

where $R_{\mathrm{calc}}(\lambda_m)$ and $R_{\mathrm{targ}}(\lambda_m)$ are the calculated and target reflect spectra of FBGS respectively, λ_m is the m simulated wavelength.

Step 4: Create a new population by repeating the following genetic operator until the new population is complete.

1. Selection: the traditional roulette select method is used with a slightly modification with the annealing process, i.e., the fitness used by the roulette selection is recalculated as

$$F' = \exp\left[\frac{F}{T}\right], \tag{4}$$

$$T = T_0 \times 0.99^{(gen-1)}, \tag{5}$$

where T is the annealing temperature, T_0 is the initial temperature, and *gen* is the current generation number.

2. Crossover: new offspring are generated using a conventional arithmetic crossover operator with a crossover probability p_c :

$$\begin{cases} O_1 = rand \cdot P_1 + (1 - rand) \cdot P_2 \\ O_2 = rand \cdot P_2 + (1 - rand) \cdot P_1 \end{cases}, \tag{6}$$

where O_1, O_2 and P_1, P_2 are offspring and parents respectively, *rand* is a random number between 0 and 1.

3. Mutation: use a multi-non-uniform mutation operator with a mutation probability P_m, mutate new offspring at every genes non-uniformly. At each gene position i, we have

$$\varepsilon_i^{'} = \begin{cases} \varepsilon_i + r \cdot \phi\left(gen, B - \varepsilon_i\right) & rand = 0 \\ \varepsilon_i - r \cdot \phi\left(gen, \varepsilon_i - A\right) & rand = 1 \end{cases}, \tag{7}$$

$$\phi\left(gen, x\right) = \left[1 - r^{\left(1 - \frac{gen}{mgen}\right)^b}\right] x, \tag{8}$$

where r is a random number in the range of [0, 1], *rand* is a random integer 0 or 1, *gen* is the current annealing generation, *mgen* is the max generation or terminate condition.

4. Elitism selection: if the highest chromosome's fitness in current generation is lower than that of last generation, the chromosome with the highest fitness from previous generation replaces that with the highest fitness of the new generation.

5. Use new generated population for a further run of algorithm. Go to step 2.

The RGA algorithm is used to demodulate two FBGs for demonstration, one with a linear strain distribution and the other with a discontinuous strain distribution. The simulation results are shown in Figs. 1–4. From the simulation results, we can see that the reconstructed strain profiles and the reflect spectra coincide with those of the FBGS's very well.

In conclusion, we developed a RGA, which is suitable for FBG distributed sensing. Only with the reflect spectrum of distributed FBGS, the strain fields distribution can be exactly demodulated even in the regions with significant strain gradients. And the numeric simulation results proved it to be an effective method for FBG distributed sensor demodulation.

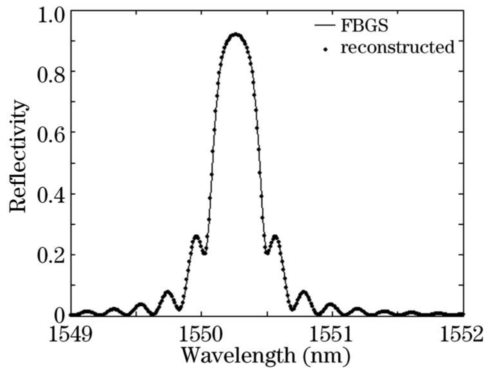

Fig. 1. Reflect spectrum of FBG with a linear strain distribution and that of the RGA reconstructed.

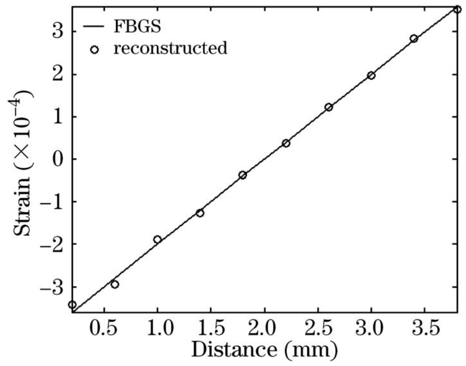

Fig. 2. Linear strain distribution of FBG and that of the RGA reconstructed.

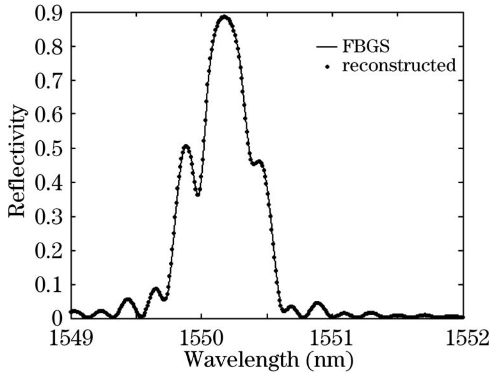

Fig. 3. Reflect spectrum of FBG with a discontinuous strain distribution and that of the RGA reconstructed.

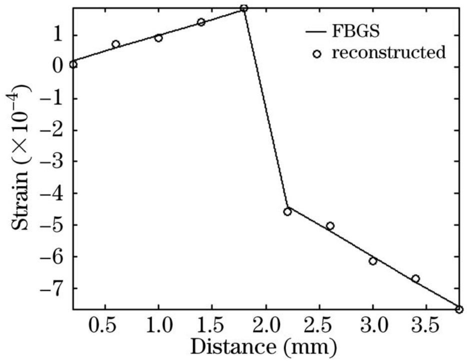

Fig. 4. Discontinuous strain distribution of FBG and that of the RGA reconstructed.

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