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A feature extraction method of the particle swarm optimization algorithm based on adaptive inertia weight and chaos optimization for Brillouin scattering spectra

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ABSTRACT

A novel particle swarm optimization algorithm based on adaptive inertia weight and chaos optimization is proposed for extracting the features of Brillouin scattering spectra. Firstly, the adaptive inertia weight parameter of the velocity is introduced to the basic particle swarm algorithm. Based on the current iteration number of particles and the adaptation value, the algorithm can change the weight coefficient and adjust the iteration speed of searching space for particles, so the local optimization ability can be enhanced. Secondly, the logical self-mapping chaotic search is carried out by using the chaos optimization in particle swarm optimization algorithm, which makes the particle swarm optimization algorithm jump out of local optimum. The novel algorithm is compared with finite element analysis-Levenberg Marquardt algorithm, particle swarm optimization-Levenberg Marquardt algorithm and particle swarm optimization algorithm by changing the linewidth, the signal-to-noise ratio and the linear weight ratio of Brillouin scattering spectra. Then the algorithm is applied to the feature extraction of Brillouin scattering spectra in different temperatures. The simulation analysis and experimental results show that this algorithm has a high fitting degree and small Brillouin frequency shift error for different linewidth, SNR and linear weight ratio. Therefore, this algorithm can be applied to the distributed optical fiber sensing system based on Brillouin optical time domain reflection, which can effectively improve the accuracy of Brillouin frequency shift extraction.

1. Introduction

Optical-fiber distributed measurement sensing is a technique which utilizes the one-dimensional nature of the optical fiber as a distinct measurement feature [1]. Because the linear relationship between temperature and Brillouin frequency shift (BFS) is the key to the Brillouin optical time domain reflectometry (BOTDR) system, scholars have proposed many different algorithms about feature extraction of Brillouin scattering spectra. For example, Chuankai Zhang et al. [2] have applied Levenberg-Marquardt (LM) algorithm to optimize the model parameters, and analyzed the nonlinear theoretical models of the Brillouin scattering spectra in BOTDR temperature sensing system. MA Farahani et al. [3] have proposed a central frequency of noisy Lorentzian curves estimation method based on the cross-correlation technique. Lijuan Zhao et al. [4] have proposed a fast and high accurate initial parameter estimation algorithm, and performed a three-parameter least-squares fitting with a LM optimization scheme to estimate the Brillouin scattering spectra parameter. Our research team [5] has proposed an improved LM algorithm based on particle swarm optimization for extracting the Brillouin scattering spectra features, and this algorithm can obtain relatively accurate solution in extracting the feature of Brillouin scattering spectra.

In order to achieve higher accuracy requirements, a novel particle swarm optimization algorithm is proposed and its significance is clearly highlighted as follows. The local search ability is reduced later in standard particle swarm optimization algorithm, and the extreme point is easily missed. Given the stochastic and ergodic characteristics of chaos variables, the chaos theory is introduced to solve this problem. In the process of particle swarm evolution, a better position particle is obtained by iteration and will be turned into a new particle by the chaotic mutation. The inertia weight affects the particles velocity between two successive iterations, and determines the algorithm performance. A single inertia weight makes the algorithm have a single search capability. Therefore, it may loss the optimal solution, or reduces the iteration speed. Combining the inertia weight with the iteration number and the adaptive value of the particle, an adaptive

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inertia weight adjustment strategy is adopted. Thereby, a PSO algorithm based on adaptive inertia weight and chaos optimization is proposed. Because this algorithm has improved the ability to get rid of the local optimal value, the novel algorithm has a good performance of global searching.

The proposed adaptive inertia weight-chaos particle swarm optimization (AIW-CPSO) algorithm is applied to the feature extraction of Brillouin scattering spectra. The estimated parameter values are comparatively accurate by the AIW-CPSO algorithm in the BOTDR system.

2. Principle and analysis method

2.1. Brillouin sensing principle

A distributed fiber sensor based on Brillouin scattering exploits the interaction of light with acoustic phonons propagating in the fiber core [6]. When the temperature of optical fiber is changed, the acoustic field velocity will be changed, and the BFS will generate. The BFS is given approximately by

$$\nu_B = 2n\nu_a/\lambda_0 \tag{1}$$

where ν_B is BFS, which is the difference between the central frequency of Brillouin scattering spectra and incident light. n is the fiber core refractive index, ν_a is the acoustic velocity in fiber and λ_0 is the wavelength of incident light in the vacuum.

For the Brillouin scattering in optical fiber, the exponential decay of acoustic waves results in a Brillouin scattering spectra, which presenting a Lorenzian spectral profile [7,8] as

$$g_B(\nu) = g_0\frac{(\Delta\nu_B/2)^2}{(\nu-\nu_B)^2 + (\Delta\nu_B/2)^2} \tag{2}$$

where ν is the Brillouin frequency, $\Delta\nu_B$ is the full-width at half maximum and g_0 is the peak value of Brillouin scattering spectra.

In order to improve the fitting accuracy of the Brillouin scattering spectra, the linear weighting combination of the Lorenz and Gauss spectra is used as the Pseudo-Voigt type fitting basis function of the Brillouin scattering spectra, and the modulation pulse width is 10 ns, that is, the spatial resolution is 1 m, and the simulation study is carried out. The improved matching function is shown as follows

$$f_B(\nu) = k\frac{(\Delta\nu_{B1}/2)^2}{(\nu-\nu_B)^2 + (\Delta\nu_{B1}/2)^2} + (1-k)\exp\left[-2.773(\nu-\nu_B)^2/\Delta\nu_{B2}^2\right] \tag{3}$$

where k is the linear weight coefficient, ν_{B1} is the Lorenz spectral linewidth and ν_{B2} is the Gauss spectral linewidth.

In the BOTDR optical fiber sensing system, temperature variation of optical fiber can produce BFS, and the change of measured temperature is linear with BFS. Therefore, the temperature can be measured by analyzing the relative changes of BFS.

2.2. Standard particle swarm algorithm

Particle swarm optimization (PSO) algorithm is based on the metaphor of social interaction and communication among different spaces in nature, such as bird flocking and fish schooling [9]. It is a swarm intelligence-based algorithm which can be used to find an optimal solution in solving optimization problems, or to establish the model and predict the social behavior in the pursuit of objectives [10]. The individual optimal solution P_{best} and the group optimal solution G_{best} are adjusted and updated dynamically by each particle as shown below.

$$\nu_{ij}(t+1) = \omega\nu_{ij} + c_1r_1(P_{besti}(t) - x_{ij}(t)) + c_2r_2(G_{besti}(t) - x_{ij}(t)) \tag{4}$$

$$x_{ij}(t+1) = x_{ij}(t) + \nu_{ij}(t+1) \tag{5}$$

where the value of i and j are $1, 2, \cdots m$ and $1, 2, \cdots n$. P_{best} is the individual extremum, G_{best} is the global extreme and ω is the inertia weight coefficient. c_1, c_2 are the acceleration constants, also called learning factors, which are the learning rates of particles in each iteration. r_1, r_2 are uniformly distributed random numbers in the region [0, 1]. ν_{ij} is the current velocity of the jth dimension in the ith particle. x_{ij} is the current position of the jth dimension in the ith particle.

2.3. Adaptive inertia weight

The inertia weight coefficient ω is utilized to influence the velocity of each particle differently over time and determines the search distance between two successive iterations [11,12]. In order to guarantee the global search ability and improve the local search ability of the algorithm, the inertia weight coefficient ω should be improved and adaptively changed.

The ω value decides the particle search speed in every iteration and it is directly related to the particle adaptive values of the current iteration number. Thus, we change the constant ω_0 value to a dynamic and adaptive one as follows:

$$p_1 = \begin{cases} \omega_0 + \dfrac{f_i - f_{avg}}{f_{max} - f_{min}} & f > f_{avg} \\ \omega_0 - \dfrac{f_{avg} - f_i}{f_{max} - f_{min}} & f \le f_{avg} \end{cases} \tag{6}$$

$$p_2 = \frac{t}{t_{max}} \tag{7}$$

$$\omega = e^{-p_2} + p_1 \tag{8}$$

where t_{max} denotes the maximum iteration number, and t represents the current iteration number. ω_0 is the initial value at iteration 1. f_i is the current fitness value of the ith particle, f_{avg} is the average fitness value of the whole group. f_{max} is the best adaptive value, and f_{min} is the worst adaptive value of particles at iteration t.

2.4. Chaos optimization

Because the information exchange of optimal solution among particles can lead to excessive concentration of particles, which makes the particles move to a certain local optimum. When a particle finds the optimal solution of rough, other particles will soon gather near this inert particle and stop during the iteration process, which can cause prematurity and then affect convergence of the algorithm [13]. To solve the problem, the chaos optimization is introduced to make the improved PSO algorithm jump out of the local optimal solution.

An essential feature of chaotic systems is that small changes in the parameters or the starting values for the data lead to vastly different future behaviors, such as stable fixed points, periodic oscillations, bifurcations, and ergodicity [14]. Chaos is a kind of irregular motion state. The chaotic state is a state of random motion which is obtained by the deterministic equation. The chaos equation used in this paper is the Logistic equation, which is a typical chaotic system and can be used to generate a series of chaotic variables. The expression is given as follows: