Damage Identification of Bridge Structures based on Improved Genetic Algorithms

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Abstract: Genetic algorithm has powerful global search ability, and its better fitness has been gradually applied to the field of civil structure damage identification. The improved genetic algorithm based on the theory of fuzzy optimization has faster convergence speed and higher operational efficiency. The improved genetic algorithm is applied to damage identification of actual bridge structures. The different data collected by various sensors are processed centrally by data fusion method, which increases the accuracy of identification results. In this paper, the displacement, stress, acceleration and other parameters collected in the field were selected to identify the damage. The feasibility of the method was verified by programming with MATLAB software.

1. Introduction

Bridge is an important part of national transportation system. Bridges may be damaged by earthquake, impact load and wind load during normal service. These factors will lead to the reduction of bearing capacity and durability of bridge structures, and even affect the normal use and operation safety. Timely, accurate and effective judgment of the location and extent of bridge damage and assessment are of great significance to the safe use of bridges. Therefore, bridge damage identification and health monitoring technology has become a hot research topic at home and abroad, and various identification methods are proposed. A structural damage identification method based on improved genetic algorithm was proposed in this paper.

Aiming at the difficulties of bridge structure damage at present, an improved multi-objective genetic algorithm based on fuzzy optimization theory was proposed. This method can effectively improve the efficiency of operation and reduce the number of genetic iterations, which can solve the huge amount of data in the process of damage identification of large structures. Researchers used Bayesian and D-S evidence theory to process decision-level fusion, and achieved good results. Data fusion theory was used to process dynamic and static indicators. Damage identification with a single parameter will lead to low accuracy of the results. Using the idea of data fusion to process the different data collected by various sensors in the region can not only improve the reliability of the results, but also detect the damage that can't be identified by a single parameter identification method.

2. Basic genetic algorithm

2.1 Concept

Genetic Algorithms (GA) is a computational model to simulate the natural selection and genetic mechanism of Darwin's biological evolution theory, which is a method to search the optimal solution by simulating the natural evolution process [1]. The operation object of genetic algorithm is a population composed of n individuals, each of which is composed of m genetic genes. Each individual makes up the search space of the problem [2]. The greater the fitness of individuals, the closer to the target value correspondingly. Population is continuously inherited and evolved through survival and development of survival of the fittest [3]. Individuals with higher fitness have greater probability to inherit to the next generation, so as to iterate continuously until the optimal individual X is obtained [4]. The basic genetic algorithm consists of three genetic operators: selection,

crossover and mutation. It is necessary to determine the coding mode, fitness function, population size, crossover and mutation probability and other parameters [5].

2.2 Development and research directions

With the expansion of the application field, there are several noticeable new trends in the research of genetic algorithm: (1) Machine learning based on genetic algorithm, this new research topic extends genetic algorithm from the traditional discrete search space optimization search algorithm to a new machine learning algorithm with unique rule generation function [6]. This new learning mechanism brings hope to solve the bottleneck problem of knowledge acquisition and knowledge optimization and refining in AI [7]. (2) Genetic algorithm is increasingly infiltrating and integrating with other intelligent computing methods such as neural network, fuzzy reasoning and chaos theory, which is of great significance to develop new intelligent computing technology in the 21st century. (3) The research of parallel genetic algorithm is very active [8]. This research is very important not only for the development of genetic algorithm itself, but also for the research of new generation intelligent computer architecture. (4) Genetic algorithm and another new research field called artificial life are constantly infiltrating. The so-called artificial life is to simulate the rich and colorful life phenomena in nature by computer. The phenomena of adaptation, evolution and immunity of organisms are the important research objects of artificial life, and genetic algorithm will play a certain role in this respect. (5) Evolution computation theories such as genetic algorithm and evolutionary programming (EP) and evolutionary strategy (ES) are increasingly integrated. EP and ES are almost independently developed with genetic algorithm [9]. Like genetic algorithm, they are also intelligent computing methods to simulate the evolution mechanism of natural organisms, that is, they have similarities with genetic algorithm and their own characteristics. At present, the comparative study and the discussion of the combination of the three are forming a hot spot.

2.3 Significance of algorithmic improvement

The genetic algorithm has the ability of global searching and individual searching synchronously in the way of population. However, the traditional genetic algorithm is applied to the damage identification of large structures, and because of the huge amount of data, the convergence speed is slow and it is easy to fall into local optimum. These problems seriously hinder the application of genetic algorithm in damage identification of large structures. In order to solve this problem, an improved algorithm based on the theory of fuzzy optimization was proposed in this paper. By parallel processing of the selection operator, the operation efficiency was greatly improved.

3. Fuzzy Optimum Selection Theory

3.1 Relative degree of superiority

Suppose that in the process of optimization and decision-making, x_{ij} is the eigenvalue of the j sub-goal for the i decision-making. In this paper, x_{ij} can be considered as the fitness value of the i individual to the damage of the j block area. If the maximum and minimum objective values of the target j in the decision set are upper and lower bounds, then the relative degree of superiority of the target is defined as follows.

(1) For the benefit-oriented objectives (maximizing the objective function):

$$r_{ij} = \left(x_{ij} - \min x_{ij} \right) \big/ \left(\max x_{ij} - \min x_{ij} \right) \tag{1}$$

(2) For cost-oriented objectives (minimizing the objective function):

$$r_{ij} = \left(\max x_{ij} - x_{ij} \right) \big/ \left(\max x_{ij} - \min x_{ij} \right) \tag{2}$$

3.2 Fuzzy optimization model for multi-objective system

The target has n sub-targets. In this paper, there are n damage areas to be identified. The

algorithm consists of m individuals. The optimization is only compared among the decision sets, so the optimization is a relative quantity. Then the evaluation objective matrix of n regions relative to m individuals is as follows:

$$\begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} = \begin{bmatrix} e_1, e_2, \cdots, e_n \end{bmatrix} \qquad (3)$$

3.3 An improved genetic algorithms based on Fuzzy Optimum Selection Theory

The optimal solution should be included in a fuzzy set. The membership function of this fuzzy set can be expressed in the formula:

$$r(a) = \sum_{i=1}^{n} \bar{\omega}_i r_i(a) \qquad (4)$$

In the formula:

$r_i(a)$ is the relative superiority of each sub-target, and i is the weight coefficient of each sub-target. The minimum solution of this membership function is the optimal solution of multi-objective system, that is, the minimum relative membership degree of m individuals relative to n subsystems.

$$r(a) = \min(r(a)) \qquad (5)$$

It can be seen from figure1 and figure 2 that the main difference between the improved algorithm and the traditional algorithm is the selection operator. The traditional selection operator determines the probability of the individual inheriting to the next generation based on the fitness value, while the improved algorithm parallels the selection operator into n groups, and the number of groups is determined by the actual problem. The value of n in this paper is determined by the number of damage identification units, and whether the selection of each sub-population is inherited to the next generation is determined by the relative superiority of fitness. It is precisely because the improved algorithm discretizes a population into n sub-groups according to the actual problem and synchronizes them, the efficiency of the algorithm is greatly improved.
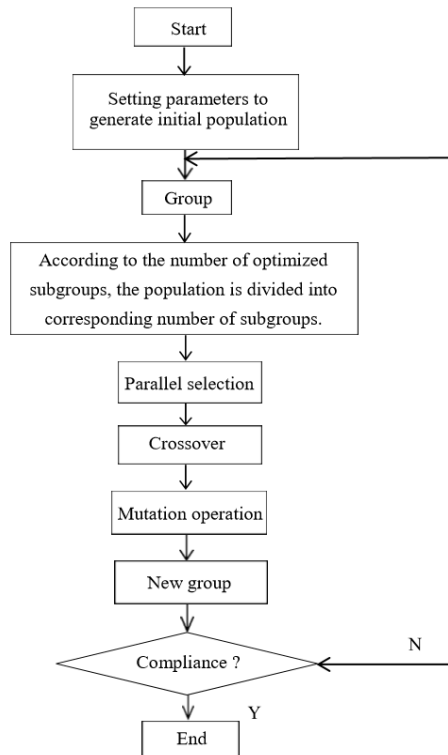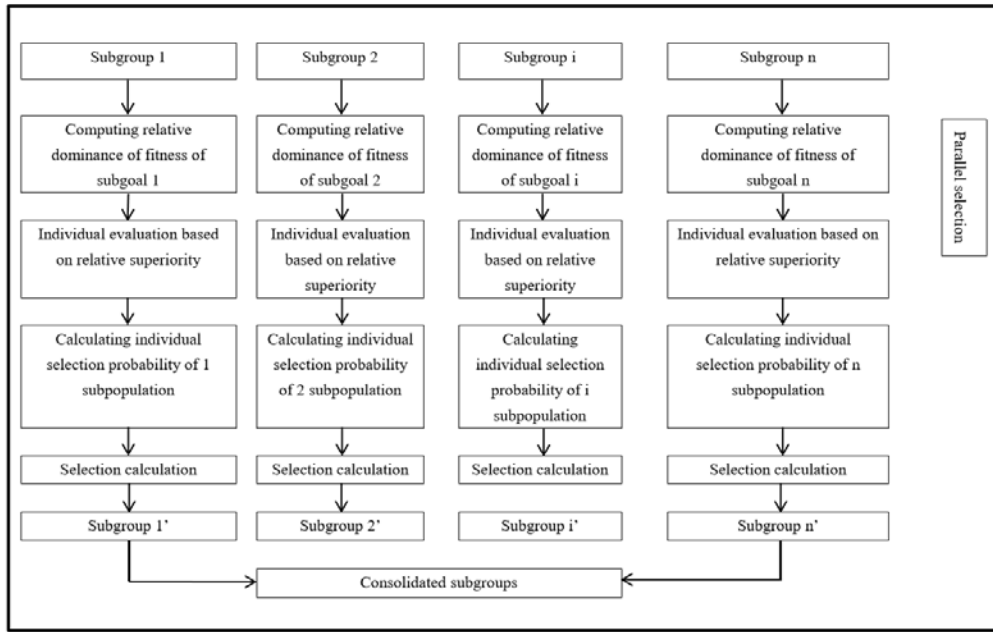

Fig.1 The flow charts of specific operations

Fig.2 The flow chart of an improved multi-objective genetic algorithm

4. Fuzzy logic data fusion

4.1 Fundamental theory

For those systems that need to collect, process and integrate multi-source data, in order to achieve autonomy and effectiveness, it is necessary to fuse incomplete or inaccurate information collected by a single sensor with data collected by other kinds of sensors to obtain more useful information. Data fusion changes the evaluation indexes of two or more different knowledge sources or sensors, which are usually given in the form of probability density function or fuzzy relation function, into a value evaluation index. This index can not only reflect the information provided by each sensor, but also reflect the information that can't be obtained only from a single data source. Fuzzy reasoning is based on the premise of fuzzy judgment, which uses the rules of fuzzy reasoning and takes the fuzzy judgment as the conclusion. Fuzzy reasoning is similar to thinking decision-making.

4.2 Fusion of fuzzy relational functions

Multiple relational functions can be fused, and the fusion result is the input function. The fusion of two fuzzy relation functions $\mu(x,y),\eta(x,y)$ is taken as an example. $\mu(x,y),\eta(x,y)$ represent the fuzzy relation functions of damage identification based on displacement and frequency modes respectively.

$$f\left[\mu(x,y),\eta(x,y)\right]=\Phi(x,y) \tag{6}$$

f is expressed by Taylor series and the higher order and constant terms are ignored.
Then, it can be obtained:

$$\Phi=\alpha\mu+\beta\eta, \quad \alpha+\beta=1 \tag{7}$$

5. Conclusions

In this paper, combining genetic algorithm and fuzzy theory, the theory of fuzzy optimization was applied to genetic algorithm, which improves the efficiency of the algorithm and makes it possible to apply to the field of damage identification of large-scale structures with large amount of data. Combining with the fuzzy logic relationship, data fusion was carried out to improve the

reliability of the damage results obtained by a single index. As a global optimization algorithm, genetic algorithm has been widely used in different fields because of its simplicity, versatility and robustness. However, there are few related literatures on the application of improved genetic algorithm to damage identification of bridge structures. There are still many problems to be further studied in the selection of parameters of genetic algorithm, operator design and cross-application with other mathematical analysis methods. In this paper, some useful research work has been done in this direction.

References

[1] Teng Zhenxin, Jiang Hua. Structural damage identification based on regularized genetic algorithm. Chongqing Architecture, 2019, 04: 37-39.

[2] Dai Lecheng, Yu Along, Zhou Xingyu, Fan Guangji. Application of improved particle swarm optimization algorithm in optimal sensor placement for bridge structural damage identification. Modern electronic technology, 2019, 4207: 133-138+152.

[3] Huang Minshui, Cheng Shaoxi, Lu Hailin. Structural damage identification considering uncertainty of temperature effect. Journal of Civil Engineering and Management, 2017, 3406: 36-40.

[4] Warriors Wang, Wang Dongdong, Gao Shengxing, Liu Kai. A dynamic evaluation method of articulated joint disease of assembled Slab-Girder Bridge Based on impact response. Journal of Civil Engineering, 2018, 5106: 103-110.

[5] He Mengyue, Liang Zhihong, Zhang Zhifang. Layered damage identification of carbon fiber reinforced composite beams based on support vector machine. FRP/composites, 2018, 07: 12-18.

[6] Liu Xiaoxia, Peng Zhenrui, Yinhong. Sensor configuration based on distribution estimation-harmony search algorithm. Journal of Lanzhou Jiaotong University, 2018, 3703: 64-70.

[7] Mao Yunxiao, Wang Yingjie, Xiao Junhua, Shijin. Bridge damage identification based on genetic algorithm of vehicle response across bridge. Vibration, test and diagnosis, 2018, 3804: 696-703+869.

[8] Zheng Guoqing, Wang Defu, Hu Junliang. Development and Prospect of Structural Damage Identification. China Shipping (second half month), 2018, 1810: 203-205.

[9] Zhang Jianwei, Jiang Qi, Liu Xuanran, Ma Xiaojun. Prediction of pipeline vibration response of cascade pumping stations based on PSO-SVM algorithm. Journal of Agricultural Engineering, 2017, 3311: 75-81.