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Hybrid intelligent algorithm and its application in geological hazard risk assessment

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ABSTRACT

This paper introduces a novel intelligent biologically inspired computational method developed to facilitate the accurate assessment of geological hazard risk (GHR). The Hybrid Intelligent Algorithm (HIA) combines Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Back Propagation (BP) neural network. GA is adopted to initialize the network connection weights and thresholds of BP and PSO is used to update them in the iteration process. In simulations based on hazard monitoring data from Jilin Province in northeastern China, the HIA method provided increased accuracy compared to established methods using BP neural networks. As GHR assessment grows in acceptance among the international risk assessment community, improved hybrid methods such as HIA will promote more effective planning in emergency response, environmental management, land use, and development.

1. Introduction

Natural hazard risk assessment has a long established history, but its related branch, geological hazard risk (GHR) assessment, is a newly-emerging research area. In recent years, theories and methods have been developed in this field to more accurately predict and analyze hazards that involve earthquakes, landslides, mudslides and other geohazards. The major findings of these GHR analyses and assessments have become the principal guidelines of hazard mitigation and rescue implementation [1]. At present, GHR assessments of most countries in the globe have adopted the following methods: Expert System [2,3], Multivariate Statistical Method [4], Geostatistics [5], Time SeriesAnalysis [6,7], Fuzzy Comprehensive Evaluation Method [8], Grey System Theory [9,10], Analytic Hierarchy Process [11–13], Gravity and Magnetic Methods [14], Back Propagation (BP) neural network, and a few of other approaches. However, these methods still remain some imperfections.

Geographic Information System (GIS) technology has become the universal application used when collecting GHR data because GIS can objectively generate hazard distribution maps, but the procedure of choosing the rational assessment model has become the major bottleneck of using GIS. The fact that geological hazards are open, nonlinear complex systems and geological processes are intricate and sophisticated which means that the dynamic information gathered from these phenomena is difficult to capture and the global optimal solution is hard to obtain. In addition, the application of a single intelligent algorithm often obtains a local optimal solution, and the number of iterations is typically quite large.

In order to address the difficulties and weaknesses mentioned above, a novel approach known as Hybrid Intelligent Algorithm (HIA) is proposed in this paper. Based on the strengths of BP algorithm's solution to nonlinear problems, Genetic Algorithm (GA) is employed to calculate initial connection weights and thresholds, and Particle Swarm Optimization (PSO) is adopted to optimize connection weights and thresholds changes in each iteration. Thus, HIA can avoid falling into a local optimal solution and improve its convergence rate and obtain more accurate results.

2. Operation principle of hybrid intelligent algorithm

2.1. Main characteristics of hybrid intelligent algorithm

BP neural network is a type of multilayer feedforward network based on the training of error back propagation algorithm and is one of the most widely used neural network model at present [15]. Its number of nodes in input layer usually takes the dimension of input vectors, while its number of nodes in output layer usually

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takes the dimension of output vectors. There is no certain standard for selecting the number of hidden nodes, and the BP will get the final result after repeated trial and error method. According to the Theorem of Kolmogorov, a 3-layer BP neural network with a hidden layer can approach to any nonlinear continuous function on a closed set with arbitrary precision if hidden layer nodes are enough. As a result, in terms of the solution of GHR assessment, one-hidden-layer is adopted in this paper. BP algorithm with a hidden layer can guarantee the network convergence after the limited iterations, but when solving nonlinear optimization problems, it can only reach a local optimum in most cases and its convergence rate is slow.

GA is a calculation model which simulates the natural selection of Darwin's biological evolution theory and the biological evolutionary process of genetic mechanism, and it is a method which searches the optimal solution via simulating natural evolutionary process [16]. After the simulation of selection, crossover and mutation mechanism in the genetic and evolutionary process, the population evolves continuously and contains the optimal or quasi-optimal solution. GA seldom traps local optimal solution in the search process, and can determine out the global optimal solution with significant probability. Therefore, GA is a typical algorithm for global optimization with good adaptability and robustness. However, because GA adopts the technology of probability searching, it has a certain degree of randomness, and the local convergence still occurs sometimes.

PSO is an evolutionary computation technology, and is developed from simulating the social behavior of birds. Similar to GA, it is an optimization algorithm based on iterations. Its system is initialized to a group of random solutions, and searches for the optimal value by iterations. But it does not use crossover and mutation of GA, its particles follow the optimal particle to search in the solution space. Compared with GA, the advantages of PSO are that it is simple and easy to be performed, and without the adjustment of several parameters [17].

Based on the above, HIA has been proposed after the improvement and integration of BP algorithm, GA and PSO. Firstly the network is trained using GA to determine a superior solution, and then the result will be trained as the network initial parameters of BP algorithm. This method can increase the classification capacity of network, so that it can avoid the local optimal solution. In this process, PSO is adopted to iterate instead of gradient decent algorithm in order to optimize connection weights and thresholds, which can significantly improve network convergence rate, thus, quickly obtain the global optimal solution.

2.2. Operation steps of hybrid intelligent algorithm

The learning process of the standard BP algorithm is the optimization learning process of two type parameters including network connection weights and thresholds. If the initial parameter selection is improper, BP algorithm is easy to fall into local optimal solution, and the default gradient descent iteration algorithm often slows the neural network convergence rate. HIA adopts GA to determine the initial parameters of the BP network in order to avoid the deficiency of BP algorithm of falling into a local optimal solution, and uses PSO to change the connection weights and thresholds in training iterations, thereby speeding up the convergence rate of the network. The specific operation steps of HIA are as follows:

(1) Determining the neural network structure, including the number of neurons in the input layer, hidden layer and output layer.

(2) *Chromosome encoding*: In the chromosome encoding process, binary encoding is usually adopted. But binary encoding in assessment of GHR will often make overlong encoding and influence the learning accuracy of network and the running time of program because of the need to convert into real number during decoding. Therefore, the real-number encoding strategy is employed [18], that is, $x=(w,\theta,v,\gamma)$, where w is the connection weight between input layer and hidden layer, θ is the threshold of hidden layer, v is the connection weight between hidden layer and output layer, and γ is the threshold of output layer.

In BP neural network, we set that the number of neurons in input layer is n, the number of neurons in hidden layer is l and the number of neurons in output layer is m. Then the connection weights and thresholds form four sets: the connection weight between input layer and hidden layer is $\{w_{ij}\}$, the threshold of hidden layer is $\{\theta_j\}$, the connection weight between hidden layer and output layer is $\{v_{ju}\}$ and the threshold of output layer is $\{\gamma_u\}$. All of the connection weights and thresholds constitute a chromosome, whose length is L,

$$L=nl+lm+m+n. \tag{1}$$

The chromosome arrangement is

$$w_{11}w_{21}\ldots w_{n1}\ldots w_{1l}w_{2l}\ldots w_{nl}v_{11}v_{12}\ldots v_{1m}\ldots v_{l1}v_{l2}\ldots v_{lm}\theta_1\theta_2\ldots\theta_l\gamma_1\gamma_2\ldots\gamma_m.$$

(3) *Building fitness function*: It is essential and necessary to select fitness function because it can directly affect convergence rate of GA and judge whether the optimal solution is reached. The target function in this paper adopts the error function E,

$$E_t=\frac{1}{2}\sum_{k=1}^{m}(c_k^{(t)}-y_k^{(t)})^2, \tag{2}$$

$$E=\frac{1}{2}\sum_{t=1}^{T}\sum_{k=1}^{m}(c_k^{(t)}-y_k^{(t)})^2=\sum_{t=1}^{T}E_t, \tag{3}$$

where E_t is the sum of the errors of each unit, $c_k^{(t)}$ is the actual output, and $y_k^{(t)}$ is the target output, T is the number of testing samples. The smaller the target function value is, the greater the fitness function is. The fitness function can be taken as $F(E)$,

$$F(E)=1/(E+1), \tag{4}$$

(4) *Establishment of selection operator*: A commonly used fitness proportional model – Monte Carlo selection [19] is adopted here. We set that the population size is G, and the fitness of the ith individual is f_i, the probability that the ith individual will be selected is P_i,

$$P_i=\frac{f_i}{\sum_{i=1}^{G}f_i}, \tag{5}$$

(5) *Design of crossover operator*: Because encoding is real-number in this paper, crossover operator uses arithmetic crossover strategy. Set two individuals as $h_A^{(i)}$ and $h_B^{(i)}$, and they are operated with arithmetic crossover. Then two new individuals $h_A^{(i+1)}$ and $h_B^{(i+1)}$ are created, that is,

$$\begin{cases} h_A^{(i+1)}=\alpha h_B^{(i)}+(1-\alpha)h_A^{(i)} \\ h_B^{(i+1)}=\alpha h_A^{(i)}+(1-\alpha)h_B^{(i)} \end{cases}, \tag{6}$$

where α is a random number which is in uniform distribution between 0 and 1.

(6) *Design of mutation operator*: Mutation operator adopts uniform mutation strategy. Set an individual as $H=h_1h_2\ldots h_k\ldots h_i$, where h_k is the mutation point and its value range is $[H_{\min}^{(k)},H_{\max}^{(k)}]$. After the uniform mutation of H at this mutation point, a new individual $H=h_1h_2\ldots h_k'\ldots h_i$ is obtained. The new gene value of the mutation point is h_k',

$$h_k'=H_{min}^{(k)}+\beta(H_{max}^{(k)}-H_{min}^{(k)}), \tag{7}$$