City Fire Forecasting Based on ACO-LSSVM

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Abstract

In order to improve the forecasting accuracy of city fire, this paper proposed a city fire forecasting method based on ant colony algorithm (ACO) and least square support vector machine (LSSVM). Firstly, the parameters of LSSVM model were considered the position vector of ants, and then target individuals which lead the ant colony to do global rapid search were determined by dynamic and stochastic extraction, and the optimal ant of this generation searched in small step nearly, lastly, the optimal parameter value was obtained by ACO and the city fire forecasting model was built. The results showed that the proposed method improves forecasting accuracy and can more accurately describe the change rule of city fire compared with traditional forecasting methods.

Keywords

Ant colony optimization algorithm, Parameter optimization, Fire forecasting Introduction.

1. Introduction

With the city's modernization process, the city having a population concentration, concentration of production, and construction concentration, fire frequency and degree of malignancy has upward trend, causing huge damage to property and to people's lives. If people can make accurate predictions of fire and make preventive measures based on predictions, which is of important practical value [1].

Currently, the traditional fire prediction methods mainly include the linear methods such as regression analysis, time series, gray systems, etc [2,3]. However, fires are affected by human factors, objective factors and social factors, having characteristics of random, sudden and non-linear, so the traditional linear prediction methods inevitably have some limitations [4]. In recent years, although the artificial neural network has a good ability of nonlinear prediction, and has made some achievements in fire prediction[5], there are some of its shortcomings which is difficult to overcome, such as complex structure network difficult to determine, over-learning, local minimum value, so it is difficult to obtain a better prediction results[6]. LSSVM, least square support vector machine， is a new artificial intelligence learning algorithms, which is able to approximate nonlinear systems with arbitrary precision, has been proven to be superior predictive artificial neural networks and other prediction methods in other areas, and provide a new method for complex fire prediction [7].

To improve the fire predictive accuracy we present an ACO-LSSVM fire prediction method, using the ant colony optimization algorithm, ACO, to optimize the LSSVM parameters, using ACO’s feedback mechanism to automatically search and optimize LSSVM parameters, establish the optimal fire prediction models, and verify its performance through concrete simulations.

2. Fire prediction principle

Fire forecast is collecting historical fire data to mine and explore, and to establish appropriate predictive models, to look for fire variation and predict fires under certain conditions precision [8]. Fire influenced by many factors, resulting such changing features as non-linear, sudden, uncertainties, so we use the following mathematical model to describe the occurrence of fire:

$$y = f(x_1, x_2, \cdots, x_n) \tag{1}$$

Among them, y is fire data, and $x_1, x_2, \cdots, x_n$ are the factors of fire. From equation (1) we can see, the fire is affected by many factors, each influencing factors are likely to have an impact on the fire, at the same time each factors have different degree influence on fire changes. So this intricate inner association determines there is a diverse, complex nonlinear relationship among the number of fires and the influencing factors, the traditional mathematical model is difficult to accurately and comprehensively considering changes in the characteristics of the fire, and it is inevitable of the emergence of large prediction errors [9].

For the complex, changing fire system, looking for a reasonable prediction model is the problem of fire prediction. LSSVM is a nonlinear and powerful predictive method, very suitable for the complicated and changeable fire system prediction, so this study uses LSSVM to predict fire. Then LSSVM can be described as:

$$y = LSSVM(x_1, x_2, \cdots, x_n) \tag{2}$$

Because LSSVM parameters have some influence on the fire prediction, so we'll use ACO optimizing LSSVM parameters, in order to further improve the accuracy of forecasting the number of fires.

3. ACO and LSSVM fire prediction

3.1 LSSVM fire prediction algorithm

For a group of fire historical sample set $\{(x_i, y_i)\}_{i=1}^{m}$, where xi is the input vector, xi∈R, yi is the corresponding output, yi ∈R, m is the sample set size. Through a nonlinear mapping function maps samples into a high dimensional feature space, then have a linear regression [10], namely

$$f(x) = \omega^T \varphi(x) + b \tag{3}$$

Where, ω is the right feature space vectors, b is offset.

According to the structural risk minimization principle, the optimization objectives of (3) are:

$$\begin{aligned} &\min J(\omega,\xi) = \frac{1}{2}\omega^T\omega + \frac{1}{2}C\sum_{i=1}^{n}\xi_i^2, \\ &\text{s.}t.y_i = \omega\varphi(x) + b + \xi_i, (i = 1,2,\ldots,\ \text{m}) \end{aligned} \tag{4}$$

Where, C is the error penalty parameters, ξ_i is the slack variables.

By introducing Lagrange multiplier the formula (4) constrained optimization problem changing into an unconstrained dual space issues, namely

$$L(\omega,\text{b},\xi,\alpha) = \frac{1}{2}\omega^{\text{T}}\omega + \frac{1}{2}C\sum_{i=1}^{n}\xi_i^2 - \sum_{i=1}^{m}\alpha_i(\omega^T\varphi(x_i) + b + \xi_i - y_i) \tag{5}$$

where α_i is Lagrange multiplier.

According to KKT conditions

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \to \omega = \sum_{i=1}^{m}\alpha_i\varphi(x_i), \\ \dfrac{\partial L}{\partial b} = 0 \to \sum_{i=1}^{m}\alpha_i\varphi(x_i) = 0, \\ \dfrac{\partial L}{\partial \xi} = 0 \to \alpha_i = C\xi_{\text{i}}, \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \to \omega^T\varphi(x_i) + b + \xi_i - y_i = 0 \end{cases} \tag{6}$$

Elimination ω and ξ_i can be

$$\begin{bmatrix} 0 & Q^T \\ Q & K+C^{-1}I \end{bmatrix} \begin{bmatrix} b \\ A \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{7}$$

For nonlinear prediction problem, by introducing the function transforming into a linear prediction problem, according to the Mercer condition, kernel function is defined as

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j) \tag{8}$$

Select the radial basis function as LSSVM kernel function, namely

$$f(x) = \sum_{i=1}^{m} \alpha_i \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \right) + b \tag{9}$$

Where σ represents the width of the kernel function, $\exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \right)$ represents radial basis function.

3.2 LSSVM parameters optimization based on ACO

In LSSVM fire forecasting process, fire prediction accuracy is mainly relevant with γ , σ values . To get better fire prediction, you must first select the most reasonable γ and σ values. ACO has better robustness, information positive feedback mechanism, and is able to find the optimal solution in a short time. So, using ACO to select γ and σ, and to reduce LSSVM parameters empirical and subjective blindness, we can further improve the prediction accuracy of fire.

3.2.1 Initializing ACO location and pheromone

For ants initial position $X_i\left(x_{i1}, x_{i2}, \cdots, x_{id}\right), i = 1, 2, \cdots, N$, the initial size pheromone of ant i is

$$\Delta\tau（i）= \exp(-f^{new}(x_i)) \tag{10}$$

When $f(X_i) \geq 0$, according to formula (11) we have seen, $\Delta\tau(i) \in (0,1]$,when $f(X_i)$ is infinity, pheromone concentration infinitely close to zero. Therefore, the corrected $f(X_i)$ is

$$f^{new}(X_i) = \begin{cases} f(X_i) / a_{vg}, 若 a_{vg} > a_{vg0} \\ f(X_i), others \end{cases} \tag{11}$$

In the formula, $f(X_i)$ and $f^{new}(X_i)$ respectively represent the individual fitness values before and after the correction, a_{vg} represents the average value of $f(X_i)$.

3.2.2 Ants build solution

When the ants complete a search, it is necessary for the next mobile search according to the rules. The mobile rules of ACO algorithm is following:

Rule 1: Randomly selecting p individuals, and then calculating the selected individual pheromone concentration, the greatest concentration of pheromone is target individuals X_{obj} .

$$X_{obj} = \begin{cases} X_j, 若 \tau(X_i) < \max(\tau(X_j)) \\ X_{best}, others \end{cases} \tag{12}$$

In the formula, X_{best} represents the optimal solution obtained in the previous iteration.

Because of the greater concentration of pheromone dependent individuals indicates the greater attracting extent to other ants, in the process of ants moving to target individuals, you may find a better solution, ant i will move to the target ants position according to equation (13).

$$X_i = (1-\lambda)X_i + \lambda X_{obj} \tag{13}$$

Ants' moving according to Rule 1 increases the randomness of the search of the algorithm in the early iteration, speed up the convergence in the post iteration.

Rule 2: For the ant X_{best} obtained optimal solution in the previous iteration, searching in its local neighborhood, the search algorithms are equation (14) and (15).

$$X_{best} = \begin{cases} X_i^{'}, 若 f(X_i^{'}) < f(X_{best}) \\ X_{best}, others \end{cases} \tag{14}$$

$$X_i^{'} = X_{best} \pm h \cdot \delta \tag{15}$$

Where, $\delta = 0.1 \times rand()$, "$\pm$" determines the search thought of the reference pattern search , judging by the following formula:

$$X_{best}^{'} = X_{best} + \left(X_{best} \cdot 0.01\right) \tag{16}$$

If $f(X_{best}^{'}) \le f(X_{best})$, select "+" ,or else select "-".

h is dynamic search step, updating by the following formula:

$$h = h_{\max} - (h_{max} - h_{\min})_{best}^{'}) \cdot \frac{i_{ter}}{i_{ter\max}} \tag{17}$$

In the formula, $h_{\max}$ and $h_{\min}$ represent the initially set constant, $i_{ter\max}$ is the maximum number of iterations, i_{ter} is the current iteration.

3.3 Pheromone update strategy

After completing the global search and local search, we'll update ant i pheromone $\tau(i)$, updating rule is:

$$\tau(i) = (1-\rho)\tau(i) + \Delta\tau(i) \tag{18}$$

Where ρ is pheromone evaporation coefficient.

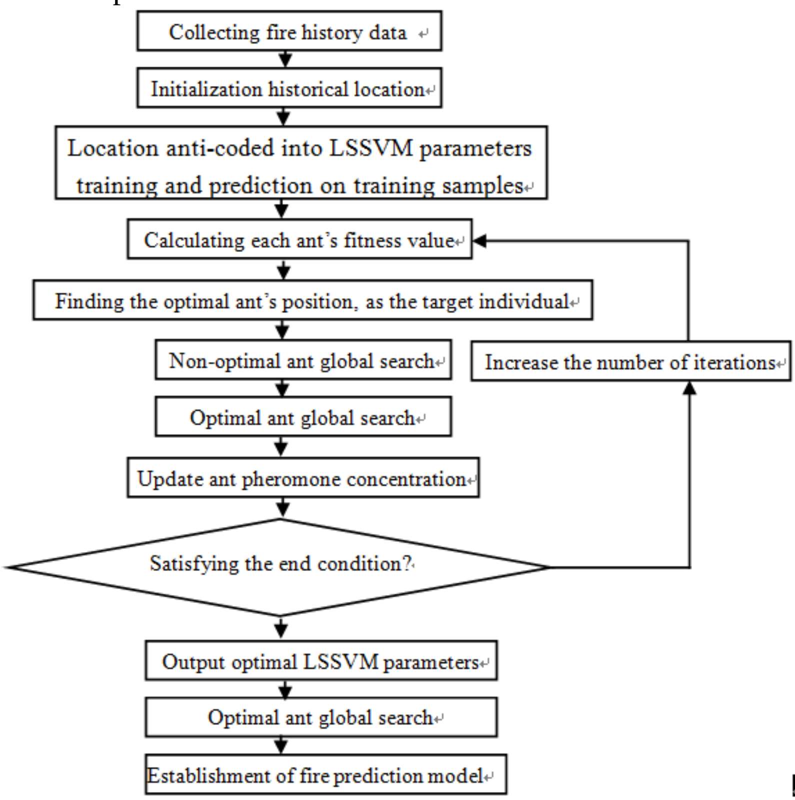

Fig. 1 Workflow of a fire prediction model

3.4 ACO and LSSVM fire forecasting process

The objective function for predicting fire is:

$$\min f(C,\sigma)=\sum_{i=1}^{M}(y_i-\hat{y}_i)^2, s.t. \begin{cases} C\in[C_{\min},C_{\max}] \\ \sigma\in[\sigma_{\min},\sigma_{\max}] \end{cases} \tag{19}$$

In the formula, y_i and y_i represent the i-th known fire prediction sample output value and the algorithm's fire prediction.

ACO and LSSVM fire forecasting process is shown in Figure 1.

4. Fire prediction's simulation

4.1 Sources of fire history data

In order to verify the validity of ACO-LSSVM algorithm, the experimental data is a city fire statistics each month of 2007-2011, total 60 data. These data constitute a one-dimensional time series of fire, as shown in Figure 2.

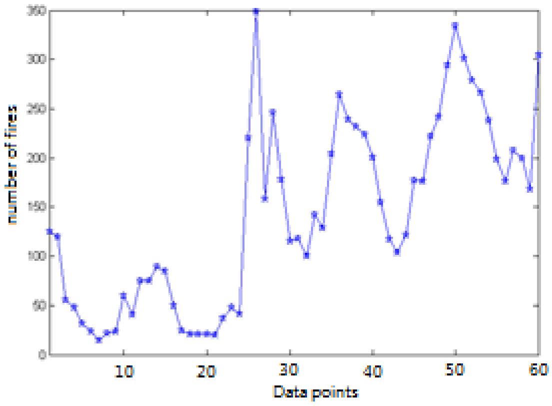

Fig.2 fire statistics data from 2007 to 2011 of a city

The data is divided into two parts: the front 48 data as the training set to establish a fire prediction model, the last 12 as a predictive data set on fire prediction model generalization capability for testing. In order to make the algorithm predicting results more explanatory, using BP neural network algorithm (BPNN) and genetic algorithm optimization LSSVM algorithm (GA-LSSVM) as a comparison model.

4.2 Fire data normalization

In order to improve the training efficiency of LSSVM, we'll make fire normalizing treatment, specifically

$$x'=\frac{x}{x_{\max}} \tag{20}$$

In the formula, x is the original fire data, $x_{\max}$ is a maximum value.

4.3 Experimental results and analysis

Since the collected fire data are a one-dimensional time series, using the each year the same month historical fire data as input, current month fire data as output, building LSSVM samples. ACO-LSSVM parameter is set to: ACO scale of 20, the size of population genetic algorithm is 20, crossover and mutation probability is individual 0.9 and 0.01, which maximum number of iterations are 200, the structure of BP neural network using 4-9-1, the maximum permissible error is 0.0001. Respectively using ACO-LSSVM, GA-LSSVM, BPNN learning training samples, and fit the training samples, predict the test samples.

4.3.1 Fire fitting results comparison

Figure 3 shows the ACO-LSSVM, GA-LSSVM and BPNN fitting results of training samples. From Figure 3, in all models, ACO-LSSVM fitted values is closest to the actual values, the highest fitting precision, which shows ACO-LSSVM has certain advantages with respect to the GA-LSSVM and BPNN model.

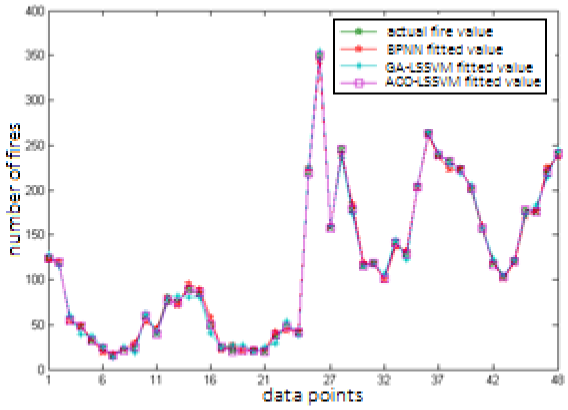

Fig.3 Fitting results of different models for training samples

4.3.2 Fire forecast results comparison

For a predictive model, the fitting result is just one aspect, the most important is the predictive ability of the model, so using the established best ACO-LSSVM, GA-LSSVM and BPNN forecasting models to predict the test samples, obtaining the predict the results is shown in Figure 4.

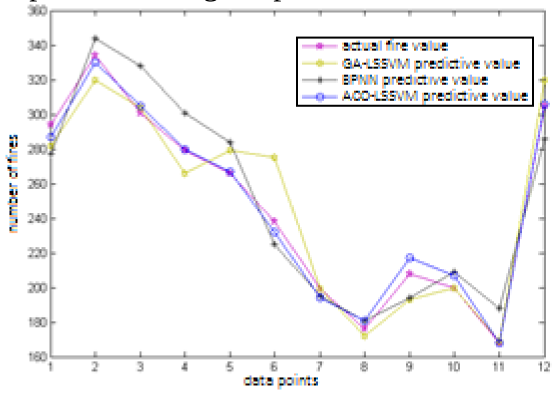

Fig.4 predict results of different models to the test samples

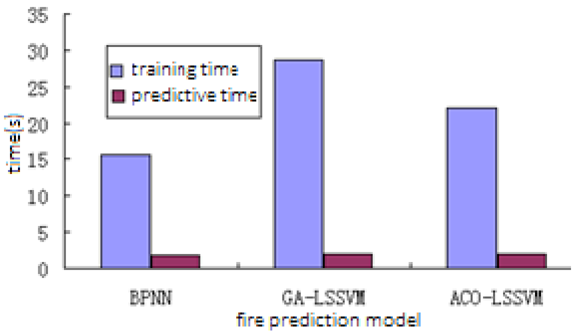

Fig.5 the speed comparison of various models prediction

Figure 4 shows that, relative to the comparison model GA-LSSVM and BPNN forecasting results, ACO-LSSVM has higher prediction accuracy, indicating the use of ACO optimizing LSSVM parameters can establish better fire prediction model. Meanwhile the generalization ability of prediction model based on LSSVM is superior to BPNN, explained LSSVM well overcome the local minima, over-fitting and other defects existing in neural networks and other traditional machine learning algorithms, and prediction results are more reliable.

Speed comparison of different fire prediction model

ACO-LSSVM, BPNN and GA-LSSVM model's running time are shown in Figure 5. Relative to the LSSVM model, BPNN has shortest training time, prediction time between the three models has little difference, but the ACO-LSSVM's running time is less than GA-LSSVM. Comparative results show that ACO using positive feedback mechanism optimizes LSSVM parameters and can find the optimal LSSVM parameters in a short period of time. Relative to the BPNN, although ACO-LSSVM need more training time, but the prediction accuracy is greatly improved.

5. Conclusions

When fire prediction is modeled, the choice of model parameters is very important to the results of the fire prediction. For the current problems of LSSVM parameters optimized, we'll use ACO with high search speed and the information positive and negative feedback mechanism optimizing LSSVM parameters, and apply to predict the fire. The results show that, ACO-LSSVM is able to accurately describe the tendency of fire, improve fire prediction accuracy and broaden the application scope of LSSVM.

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