



Application of GA-SVM method with parameter optimization for landslide development prediction

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Abstract

Prediction of landslide development process is always a hot issue in landslide research. So far, many methods for landslide displacement series prediction have been proposed. Support vector machine (SVM) has been proved to be a novel algorithm with good performance. However, the performance strongly depends on the right selection of the parameters (C and γ) of SVM model. In this study, we presented an application of GA-SVM method with parameter optimization in landslide displacement rate prediction. We selected a typical large-scale landslide in some hydro - electrical engineering area of Southwest China as a case. On the basis of analyzing the basic characteristics and monitoring data of the landslide, a single-factor GA-SVM model and a multi-factor GA-SVM model of the landslide were built. Moreover, the models were compared with single-factor and multi-factor SVM models of the landslide. The results show that, the four models have high prediction accuracies, but the accuracies of GA-SVM models are slightly higher than those of SVM models and the accuracies of multi-factor models are slightly higher than those of single-factor models for the landslide prediction. The accuracy of the multi-factor GA-SVM models is the highest, with the smallest RSME of 0.0009 and the biggest RI of 0.9992.

1 Introduction

Prediction of landslide development process is a critical task in landslide research (Sornette et al., 2004; Helmstetter et al., 2004; Corominas et al., 2005; Gao, 2007). Accurate prediction can provide a scientific guide to landslide pre-warning and forecast and engineering control as quickly as possible. However, it is not easy to accurately predict the evolution behavior of landslides. This is mainly because of geometrical complexity, non-linearity of the displacement – time relationships and a large number of interplay factors, hardly taken into account by prediction models (Crosta and Agliardi, 2002).

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The most common method of predicting the development process is to build suitable models according to the development mechanism and monitoring data of landslides. So far, many models have been put forward (Saito, 1965; Voight, 1989; Crosta and Agliardi, 2002; Lu and Rosenbaum, 2003; Feng et al., 2004; Helmstetter et al., 2004; Neaupane and Achet, 2004; Sornette et al., 2004; Randall, 2007; Mufundirwa et al., 2010). They can be roughly classified into four categories: deterministic physical models, statistics models, nonlinear models and numerical simulation models (Li et al., 2012). In them, the nonlinear models are considered to have the potential for coping with difficult and complicated problems. Especially, artificial intelligence methods representing with neural networks (NN) have been widely used in landslide prediction recently (Lu and Rosenbaum, 2003; Neaupane and Achet, 2004). However, some problems have appeared in the practical applications of NN methods because of its imperfect theory, such as being suitable only for large data sets and easily occurring local minimum and having weak generalization ability. Therefore, we need to find a better method for landslide development prediction.

Support vector machine (SVM) is a new machine learning method originally developed by Vapnik and his co-workers. The method works on Vapnik–Chervonenkis (VC) dimension theory of statistic learning theory (SLT) and structural risk minimization principle (Cortes and Vapnik, 1995). It seeks an optimal compromise between the complexity and learning capacity of models according to limited samples, in order to obtain best generalization ability (Cortes and Vapnik, 1995; Cristianini and Shawe-Taylor, 2000). It can preferably resolve small sample, non-linear and high dimensions problem. So, the method has been widely used in the fields of classification and regression (Oliveira et al., 2004; Khan et al., 2006). Recently, a few researchers have begun to try to apply the method in landslide and slope research. For example, Yao et al. (2008), Ballabio and Marjanovic (2011) and Sterlacchini et al. (2012) applied it to landslide susceptibility mapping and assessment, and obtained better results. Samui (2008) used it to predict safety status and factors of slopes, and indicated that SVM model gives better result than the result of ANN for safety factor prediction of slopes.

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Although SVM has been widely used in some fields, its application effect is far from its theory expected effect. According to the related references (Cherkassky and Ma, 2004; Lessmann et al., 2005; Min and lee, 2005), the selection of kernel functions and parameters is one of main reasons affecting the application effect. At present, parameters of SVM model are manually selected by experiences, lack of the instruction of mature theory. Genetic Algorithm (GA) is a global optimization algorithm with good robustness, which was first suggested by John Holland, 1975. GA can be used to automatically recognize some parameters of SVMs (Lessmann et al., 2005; Pourbasheer et al., 2009). So, we presented an application of GA-SVM in landslide development prediction.

The paper is organized as follows. Section 1 starts with literature associated with landslide development prediction and features and applications of related prediction methods. Section 2 introduces SVM, GA and GA-SVM methods. Section 3 presents a typical large-scale landslide case. Application results are described in Sect. 4. Discussion and conclusions are presented in Sect. 5.

2 Methodology

2.1 SVM for regression

As the detailed description of SVM theory can be found in various references (e.g. Cortes and Vapnik, 1995; Cristianini and Shawe-Taylor, 2000), Here, we only introduce some key points of SVM for regression (SVMR).

SVMR has two types: linear regression and nonlinear regression. For linear regression, first considering the problem using a linear regression function

$$f(\mathbf{x}) = \boldsymbol{\omega} \times \mathbf{x} + b \quad (1)$$

to fit the data $\{\mathbf{x}_i, y_i\}, i = 1, 2, \dots, n, \mathbf{x}_i \in \mathbf{R}^n, y_i \in \mathbf{R}$, where, $\boldsymbol{\omega}$ is an adjustable weight vector, b is scalar threshold, \mathbf{x} is the input and y is the output, \mathbf{R}^n is n -dimensional

vector space and R is one dimensional vector space. In order to find a function as flat as possible $f(x)$ that gives a deviation ε from the actual output (y), a smallest ω need be found. It can be obtained by minimizing the Euclidean norm $\|\omega\|^2$ (Smola and Scholkopf, 2004; Samui, 2008). This can be written into a convex optimization problem as follows:

$$\begin{aligned} & \text{Minimize } \frac{1}{2} \|\omega\|, \quad (i = 1, 2, \dots, n) \\ & \text{Subject to } \begin{cases} y_i - \langle \omega \times x_i \rangle - b \leq \varepsilon \\ \langle \omega \times x_i \rangle + b - y_i \leq \varepsilon \end{cases} \end{aligned} \quad (2)$$

Considering the existence of some permissible error, slack variables ξ_i and ξ_i^* are introduced into the above optimization problem. Equation (2) becomes:

$$\begin{aligned} & \text{Minimize } \frac{1}{2} \|\omega\| + C \sum_{i=1}^n (\xi_i + \xi_i^*), \\ & \text{Subject to } \begin{cases} y_i - \langle \omega \times x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle \omega \times x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (i = 1, 2, \dots, n), \end{aligned} \quad (3)$$

where the constant $C > 0$ shows the penalty degree of the sample with error exceeding ε and is called as penalty factor.

A dual problem of Eq. (3) can be obtained by using the optimization method.

$$\begin{aligned} & \text{Maximize : } W(a, a^*) = -\frac{1}{2} \sum_{i,j=1}^n (a_i - a_i^*)(a_j - a_j^*)(x_i \times x_j) + \sum_{i=1}^n y_i(a_i - a_i^*) - \varepsilon \sum_{i=1}^n (a_i + a_i^*), \\ & \text{Subject to : } \begin{cases} \sum_{i=1}^n (a_i - a_i^*) = 0 \\ a_i \geq 0 \\ a_i^* \leq C \end{cases} \quad i = 1, 2, \dots, n, \end{aligned} \quad (4)$$

where a_i, a_i^* are Lagrange multipliers.

Solving the above optimization problem, the fitness function of SVM can be given by:

$$f(\mathbf{x}) = \omega \times \mathbf{x} + b = \sum_{i=1}^k (a_i - a_i^*)(\mathbf{x}_i \times \mathbf{x}) + b, \quad (5)$$

- 5 where k is the number of support vectors, the samples (\mathbf{x}_i, y_i) corresponding to $a_i - a_i^* \neq 0$ are support vectors.

For nonlinear problem, the origin problem can be mapped into a high dimension feature space by some nonlinear transformation (Cristianini and Shawe-Taylor, 2000). In the feature space, the inner product operation of linear problem can be substituted by kernel functions, i.e. $K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i) \cdot \varphi(\mathbf{x}_j)$. Therefore, Eqs. (4) and (5) can be written as:

$$\begin{aligned} \text{Max : } W(\mathbf{a}, \mathbf{a}^*) &= -\frac{1}{2} \sum_{i,j=1}^n (a_i - a_i^*)(a_j - a_j^*)K(\mathbf{x}_i, \mathbf{x}_j) + \sum_{i=1}^n y_i(a_i - a_i^*) - \varepsilon \sum_{i=1}^n (a_i + a_i^*) \\ \text{S.T. : } &\begin{cases} \sum_{i=1}^n (a_i - a_i^*) = 0 \\ a_i \geq 0 \\ a_i^* \leq C \end{cases} \quad i = 1, 2, \dots, n, \end{aligned} \quad (6)$$

$$f(\mathbf{x}) = \omega \times \mathbf{x} + b = \sum_{i=1}^n (a_i - a_i^*)K(\mathbf{x}_i, \mathbf{x}) + b, \quad (7)$$

- 15 where $K(\mathbf{x}_i, \mathbf{x})$ is a kernel function which measures the similarity of distance between the input vector \mathbf{x}_i and the stored training vector \mathbf{x} (Feng et al., 2004). The meanings of other parameters are same to the parameters mentioned above.

At present, four basic kernel functions have been widely used. They are (Cristianini and Shawe-Taylor, 2000):

linear : $K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i, \mathbf{x}_j)$.

polynomial : $K(\mathbf{x}_i, \mathbf{x}_j) = [\gamma \cdot (\mathbf{x}_i, \mathbf{x}_j) + 1]^d, \gamma > 0$.

5 radial basis function (RBF) : $K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma \cdot \|\mathbf{x}_i - \mathbf{x}_j\|^2\right)$.

sigmoid kernel : $K(\mathbf{x}_i, \mathbf{x}_j) = \tanh[\gamma(\mathbf{x}_i, \mathbf{x}_j) + r]$.

Here, γ , r , and d are kernel parameters. In this study, we mainly used RBF as kernel function of SVM model for landslide prediction, because the function has strong
10 nonlinear mapping ability.

2.2 Genetic algorithm (GA)

GA, an adaptive optimizing method with overall searching function, is devised by simulating the genetic evolution mechanism of biology in natural environment (Whitley, 1994). The method simulates the copying, crossing and variation phenomena in the
15 process of natural selection and heredity. Starting from any initial population, a group of new better – adapted individuals can be generated by randomly selecting, crossing and variation operation. So, by unceasing evolution from generation to generation, a best – adapted individual (the optimal solution of optimal problem) can be acquired at last. It has the advantages of global optimality, implicit parallelism, high stability and wide usability. The method has been widely used in computer, engineering technique,
20 management and social science (Lessmann et al., 2005; Pourbasheer et al., 2009; Choudhry and Garg, 2009). In this study, we mainly use GA to search for the parameters (C and γ) of SVM model for landslide development prediction.

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2.3 GA-SVM model

In order to build an effective SVM model, the parameters (C and γ) of the model need to be chosen properly in advance (Lin, 2001). The parameter C , determines the tradeoff cost between minimizing the training error and complexity of SVM model. The bigger C value, predictive accuracy of the training sample is higher. However, this may cause an over-training problem. The parameter γ of RBF kernel function defines a non-linear mapping from input space to high – dimensional feature space. The value of γ affects the shape of RBF function. So, the parameters (C and γ) have a powerful influence on the efficiency and generalization performance of SVM model. At present, the choice of the parameters lacks the guide of mature theory, mainly depending on experiences. A grid-search technique was presented by Lin (2001). However, the grid algorithm is time consuming and does not perform very well (Gu et al., 2011).

According to some related research in different fields, GA is proved to be a better choice to determine the parameters (Lessmann, 2005; Pourbasheer et al., 2009). It can reduce the blindness of man-made choice and improve the predicative performance of SVM model. Therefore, we choose GA to search for the optimal parameters of SVM model for landslide prediction in this study. The basic flowchart of GA-SVM method can be seen in Fig. 1.

The algorithm can be realized by a parameter optimization procedure designed by Y. Li of Beijing Normal University based on the libsvm-mat toolbox, which is developed by Lin of National Taiwan University.

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3 Landslide case study

Here, we selected a typical large-scale landslide in Southwest China as a case.

3.1 Basic characteristics of the landslide

The landslide is located on the left bank of reservoir head of some hydro – electrical power station in Southwest China, which is about 600 m away from the axis of the reservoir dam. The origin slope in landslide area belongs to monoclinic dip slope, with the slope height of 500–700 m, the average width of about 700 m and the volume of 5 million m³. The slope direction is 210–215°. The landslide body borders 1400 m elevation, the terrain lower than the elevation is gentle, with an average gradient of 22–25°, while the terrain higher than the elevation is steeper, with a gradient of 35–45°. The landslide has three free faces, and there are several gullies and multi-level gentle slopes on the uneven slope face (Fig. 2).

The top of landslide body is composed of a set of basalt with block structure, its bottom is composed of a set of sedimentary rock with layer structure. The landslide body can be divided into three zones from upstream to downstream, according to lithology and material composition characteristics and the continuity of the slip surface. Zone I, an ancient landslide area, is located in the upstream side of the landslide, with a trench and valley landform. Zone II, creep area of rock body which is main deformation area of the landslide, is located in the middle of the landslide, with a ridge landform. Zone III, shallow – surface landslide area, is located in the downstream side of the landslide, with a ridge landform (Fig. 2). Our research focus on the Zone II.

In order to ascertain the basic characteristics of the landslide and evaluate its stability and development tendency, an overall monitoring system was established in April 1998. The monitoring items include precise geodetic survey, drilling monitoring, footrill monitoring, meteorological observations and engineering geological survey and so on. So far, we have accumulated a large number of detailed monitoring data for the landslide.

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3.2 Monitoring data of the landslide

We choose the footrill monitoring data of the creep body in zone II from April 1998 to December 2005 to deeply analyze the relationships between the landslide displacement rate and rain, reservoir water and groundwater. The displacement rate is calculated on the basis of the monitoring displacement values. For contrast, the index values are normalized by minimax method. The analysis results are shown in Figs. 3–5.

Figure 3 shows that there is a good relationship between landslide displacement rate and rainfall, and the peaks of the displacement rate generally lag behind the rainfall peaks. As can be seen from Fig. 4, the impact of reservoir water level changes on the landslide mainly manifests in the early stages of storing water. The displacement rate of the landslide increased significantly after the reservoir started to store water in 1998. Afterwards, the impact of the reservoir water level on the landslide gradually decreased. The changes of the displacement rate showed a gradual decrease trend with the fluctuations of the water level. Figure 5 shows that there is a very significant relationship between groundwater flow and the displacement rate. They had a good consistency and almost reached peak level at the same time.

Based on the above analysis results and the engineering geological survey results, the development process of the landslide is affected by the rain, reservoir water and other predisposing factors on the whole. But, the deformation is mainly affected by rainfall conditions, except that the changes of reservoir water level had a powerful effect on the landslide in the early stages of storing water.

4 Application results

In this section, we will analyze the development tendency of the landslide, based on the above-mentioned GA-SVM method and the monitoring data analysis results. We respectively built a single-factor GA-SVM model and a multi-factor GA-SVM model for the landslide.

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4.1 Single-factor GA – SVM prediction result

Firstly, we take the average monthly displacement rate from April 1998 to December 2005 of the landslide (93 data) as a factor of building model. The previous 62 data were chosen as training samples, and the other 31 data were considered as test samples. We built a single-factor SVM model for the landslide development prediction, and determined the parameters (C and γ) of the model by GA. The GA had a generation number of 100, population size of 20. The search range of C and γ parameters is [0, 100]. The process searched optimal parameters by GA can be seen in Fig. 6. We obtained best C parameter 7.9155, best γ parameter 0.13504. The model with the best parameters has the smallest mean square error (MSE). The prediction result of the GA-SVM model with the optimal parameters is shown in Fig. 7.

Figure 7 shows that the monitoring data have a good agreement with the prediction result of the single-factor GA-SVM model.

4.2 Multi-factor GA – SVM prediction result

Secondly, we take the average monthly displacement rate, average monthly reservoir water level, monthly rainfall and average monthly groundwater flow from April 1998 to December 2005 of the landslide as main factors of building model. Similarly, the previous 62 data of the four factors were chosen as training samples, and the other 31 data of the four factors were considered as test samples. We also built a multi-factor SVM model for the landslide development prediction, and determined the parameters (C and γ) of the model by GA. The parameters of GA and the search range of C and γ parameters identity with those of the single-factor GA-SVM. The process of obtaining the parameters and the prediction results of this model can be seen in Figs. 8 and 9.

Figure 9 also shows that the monitoring data have a good agreement with the prediction result of the multi-factor GA-SVM model.

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4.3 Comparison of GA-SVM and SVM prediction results

In order to evaluate the prediction performance of the above GA-SVM models, we also built single-factor and multi-factor SVM models of the landslide by using the same training samples as the GA-SVM models, and obtained the model parameters (C and γ) by using the grid – search method (Figs. 10 and 11).

The prediction accuracy of the SVM and GA-SVM models can be evaluated by two indexes. They are respectively Root Mean Square Error (RMSE) and Relation Index (RI). Generally, the smaller RSME and the bigger RI, the higher the accuracy of the model is. They can be calculated by using the following formulas (Li et al., 2012):

$$10 \quad \text{RSME} = \sqrt{\frac{\sum_{k=1}^n (X^{(0)}(k) - \hat{X}^{(0)}(k))^2}{n}}, \quad (8)$$

$$\text{RI} = \sqrt{1 - \frac{\sum_{k=1}^n (X^{(0)}(k) - \hat{X}^{(0)}(k))^2}{\sum_{k=1}^n (X^{(0)}(k) - \bar{X}^{(0)})^2}}. \quad (9)$$

where $X^{(0)}(k)$ is the observed value and $\hat{X}^{(0)}(k)$ is the predicted value of the models, n and $\bar{X}^{(0)}$ are the size and average value of the data sequence $X^{(0)}(k)$.

15 The prediction accuracy indexes of the models are shown in Table 1. As can be seen from Table 1, the prediction models have much higher accuracies, and the RI values between the predicting and monitoring values reach 0.99. The accuracies of GA-SVM models are slightly higher than those of SVM models, and the accuracies of multi-factor models are slightly higher than those of single-factor models. Among the models, the accuracy of the multi-factor GA-SVM models is the highest, with the smallest RSME of 0.0009 and the biggest RI of 0.9992.

5 Discussion and conclusions

SVM is a new machine learning method with good performance. However, the generalization performance of SVM models strongly depends on the right choose of the parameters (C and γ) (Cherkassky and Ma, 2004; Lessmann et al., 2005). In this study, we took a complicated large-scale landslide in some hydro – electrical engineering area of Southwest China as a case, to present an application of GA-SVM method with parameter optimization in landslide displacement rate prediction. GA and SVM are organically combined by using GA to automatically search for the parameters of the single-factor and multi-factor SVM models of the landslide.

In addition, we also built the single-factor and multi-factor traditional SVM models of the landslide prediction. By comparing, we find that the accuracies of GA-SVM models are lightly higher than those of SVM models and the accuracies of multi-factor models are slightly higher than those of single-factor models for the landslide prediction. Among the models, the accuracy of the multi-factor GA-SVM models is the highest, with the smallest RSME of 0.0009 and the biggest RI of 0.9992.

Therefore, the application results indicate that SVM and GA-SVM models have good prediction performance for landslide development tendency, and GA is an effective way for the parameters selection of SVM models. Because of the complexity of landslides and diversity and randomness of its influence factors, the application of SVM and GA-SVM methods in the landslide development prediction has significant potential.

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- Ballabio, C. and Sterlacchini, S.: Support Vector Machines for Landslide Susceptibility Mapping: The Staffora River Basin Case Study, Italy, *Math. Geosci.*, 44, 47–70, 2012.
- Chang, C. C. and Lin, C. J.: LIBSVM: a library for support vector machines, *ACM Trans. Int. Syst. Technol.*, 2, 1–39, 2001.
- Cherkassky, V. and Ma, Y.: Practical selection of SVM parameters and noise estimation for SVM regression, *Neural Networks*, 17, 113–126, 2004.
- Choudhry, R. and Garg, K.: A hybrid machine learning system for stock market forecasting, *World Academy of Science, Eng. Technol.*, 39, 315–318, 2009.
- Corominas, J., Moya, J., Ledesma, A., Lloret, A., and Gili, J. A.: Prediction of ground displacements and velocities from groundwater level changes at the Vallcebre landslide (Eastern Pyrenees, Spain), *Landslides*, 2, 83–96, 2005.
- Cortes, C. and Vapnik, V.: Support-vector networks, *Machine Learning*, 20, 273–297, 1995.
- Cristianini, N. and Shawe-Taylor, J.: An introduction to support vector machines and other kernel-based learning methods, Cambridge university press, 2000.
- Crosta, G. B. and Agliardi, F.: How to obtain alert velocity thresholds for large rockslides, *Phys. Chem. Earth*, 27, 1557–1565, 2002.
- Feng, X. T., Zhao, H. B., and Li, S. J.: Modeling non-linear displacement time series of geomaterials using evolutionary support vector machines, *Int. J. Rock Mech. Mining Sci.*, 41, 1087–1107, 2004.
- Gao, W.: Study on displacement prediction of landslide based on grey system and evolutionary neural network, *Comput. Methods Eng. Sci.*, 275–275, doi:10.1007/978-3-540-48260-4_121, 2007.
- Gu, J., Zhu, M., and Jiang, L.: Housing price forecasting based on genetic algorithm and support vector machine, *Expert Syst. Applications*, 38, 3383–3386, 2011.
- Helmstetter, A., Sornette, D., Grasso, J. R., Andersen, J. V., Gluzman, S., and Pisarenko, V.: Slider-Block Friction Model for Landslides: Application to Vaiont and La Clapiere Landslides, *J. Geophys. Res.*, 109, 1–15, 2004.
- Khan, M. S. and Coulibaly, P.: Application of Support Vector Machine in Lake Water Level Prediction, *J. Hydrol. Eng.*, 11, 199–205, 2006.
- Lessmann, S., Stahlbock, R., and Crone, S. F.: Optimizing hyperparameters of support vector machines by genetic algorithms, In *IC-AI*, 74–82, 2005.

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- Li, X. Z., Kong, J. M., and Wang, Z. Y.: Landslide displacement prediction based on combining method with optimal weight, *Nat. Hazards*, 61, 635–646, 2012
- Lin, P. T.: Support vector regression: Systematic design and performance analysis, Unpublished Doctoral Dissertation, Department of Electronic Engineering, National Taiwan University, 2001.
- Lu, P. and Rosenbaum, M. S.: Artificial neural networks and grey systems for the prediction of slope stability, *Nat. Hazards*, 30, 383–398, 2003.
- Marjanovic, M., Kovacevic, M., Bajat, B., and Vozenilek, V.: Landslide susceptibility assessment using SVM machine learning algorithm, *Eng. Geol.*, 123, 225–234, 2011.
- Min, J. H. and Lee, Y. C.: Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters, *Expert Syst. Appl.*, 28, 603–614, 2005.
- Mufundirwa, A., Fujii, Y., and Kodama, J.: A new practical method for prediction of geomechanical failure-time, *Int. J. Rock Mech. Mining Sci.*, 47, 1079–1090, 2010.
- Neaupane, K. M. and Achet, S. H.: Use of backpropagation neural network for landslide monitoring: a case study in the higher Himalaya, *Eng. Geol.*, 74, 213–226, 2004.
- Oliveira, L. S. and Sabourin, R.: Support Vector Machines for Handwritten Numerical String Recognition, Ninth International Workshop on Frontiers in Handwriting Recognition, 39–44, 2004.
- Pourbasheer, E., Riahi, S., Ganjali, M. R., and Norouzi, P.: Application of genetic algorithm-support vector machine (GA-SVM) for prediction of BK-channels activity, *Euro. J. Medicinal Chem.*, 44, 5023–5028, 2009.
- Randall, W. J.: Regression models for estimating coseismic landslide displacement, *Eng. Geol.*, 91, 209–218, 2007.
- Saito, M.: Forecasting the time of occurrence of a slope failure, *Proceedings of the 6th International Conference on Soil Mechanics and Foundation Engineering*, Montréal, Que, Pergamon Press, Oxford, 537–541, 1965.
- Samui, P.: Slope stability analysis: a support vector machine approach, *Environ. Geol.*, 56, 255–267, 2008.
- Smola, A. J. and Scholkopf, B.: A tutorial on support vector regression, *Stat. Comput.*, 14, 199–222, 2004.
- Sornette, D., Helmstetter, A., Andersen, J. V., Gluzman, S., Grasso, J. R., and Pisarenko, V.: Towards landslide predictions: two case studies, *Phys. A*, 338, 605–632, 2004.

- Voight, B.: A relation to describe rate-dependent material failure, Science (Washington, DC), 243, 200–203, 1989.
- Whitley, D.: A genetic algorithm tutorial, Stat. Comput., 4, 65–85, 1994.
- Yao, X., Tham, L. G., and Dai, F. C.: Landslide susceptibility mapping based on Support Vector Machine: A case study on natural slopes of Hong Kong, China, Geomorphology, 101, 572–582, 2008.

NHESSD

1, 5295–5322, 2013

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Table 1. The accuracy comparison of the SVM and GA-SVM models for the landslide.

Evaluation index	SVM model		GA-SVM model	
	Single factor	Multi factors	Single factor	Multi factors
RMSE	0.0026	0.0013	0.0010	0.0009
RI	0.9935	0.9984	0.9989	0.9992

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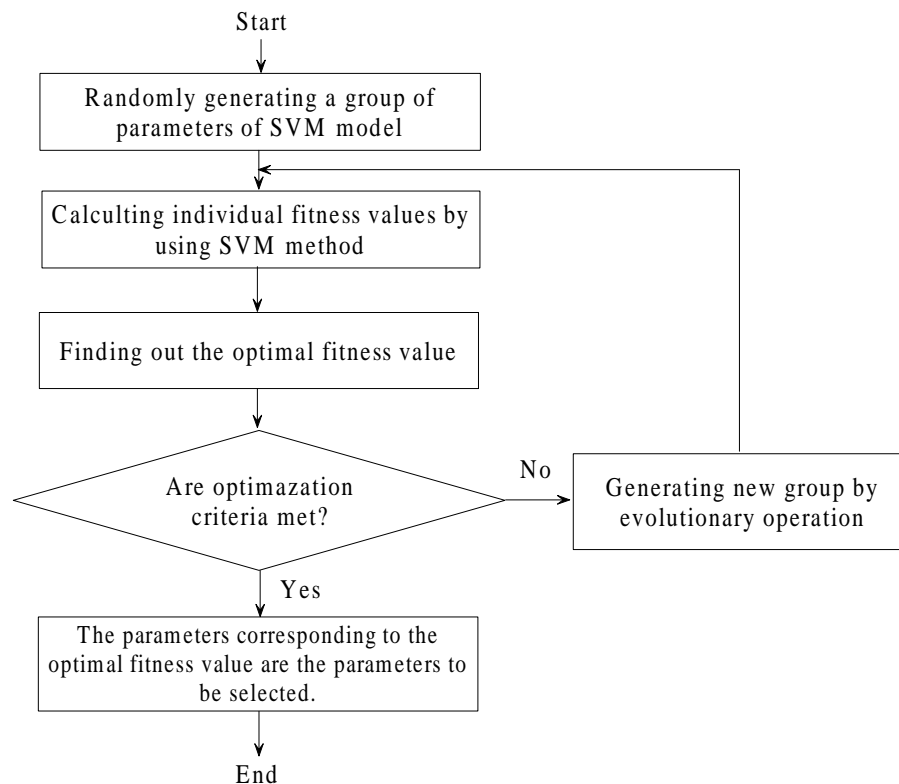


Fig. 1. Basic flowchart of GA-SVM method.

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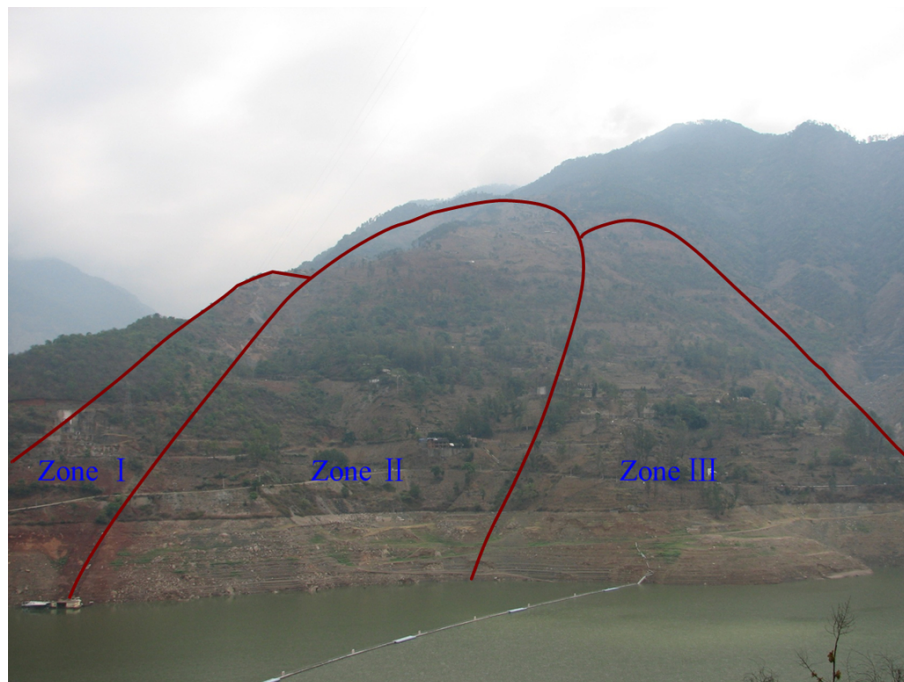
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**Fig. 2.** The whole view of the landslide.

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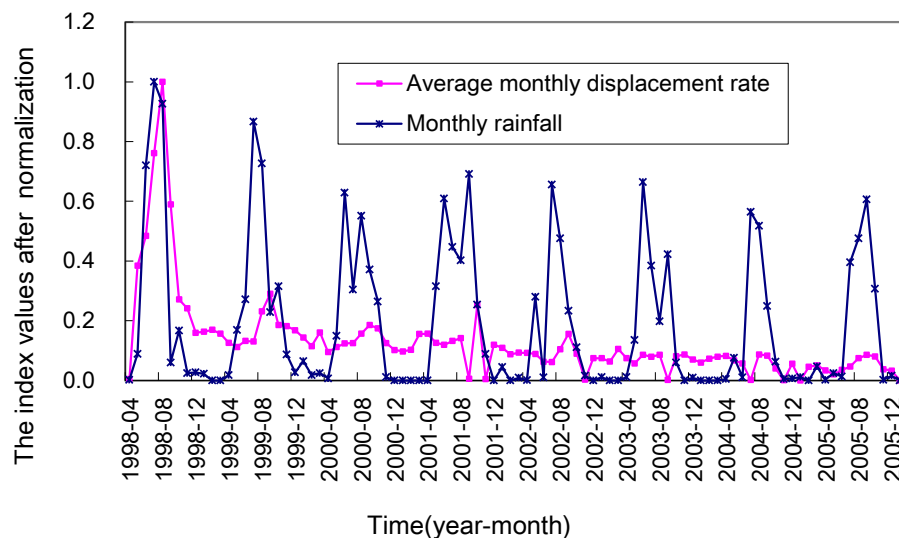


Fig. 3. The relationship between the displacement rate and rainfall for the landslide.

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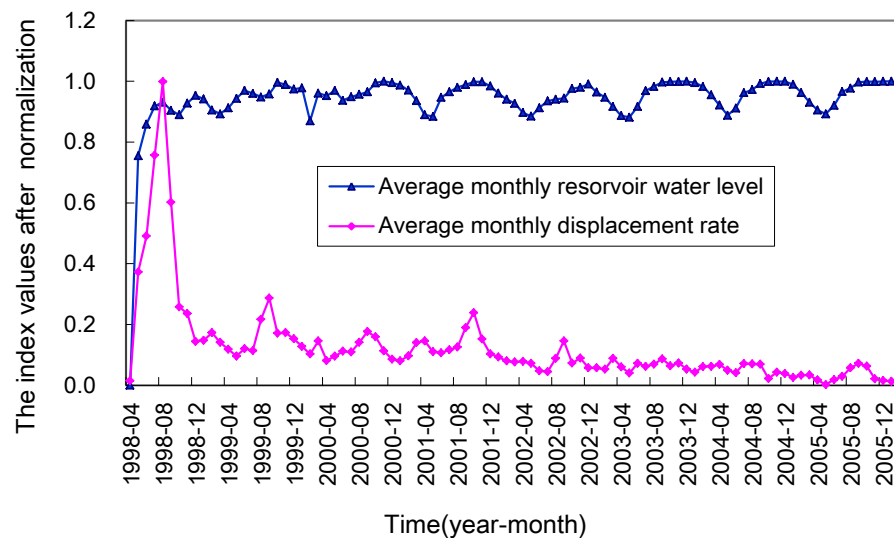


Fig. 4. The relationship between the displacement rate and reservoir water level for the landslide.

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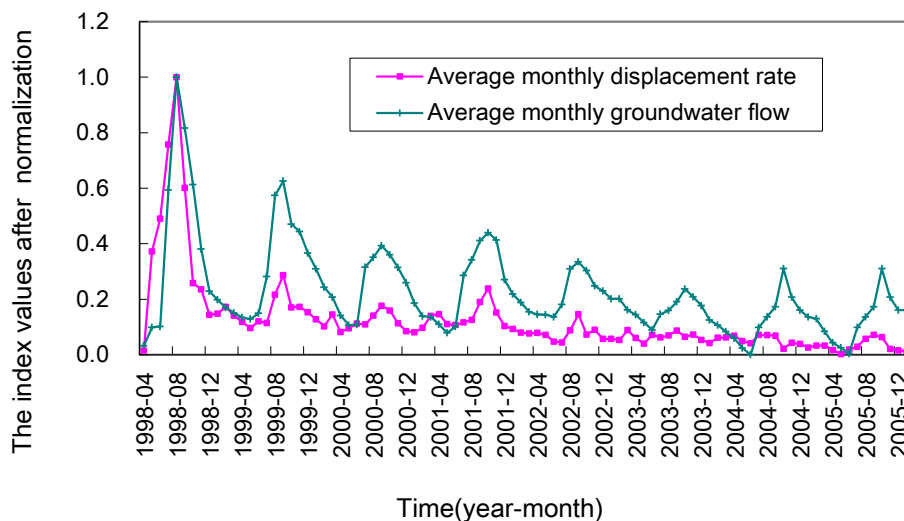


Fig. 5. The relationship between the displacement rate and groundwater flow for the landslide.

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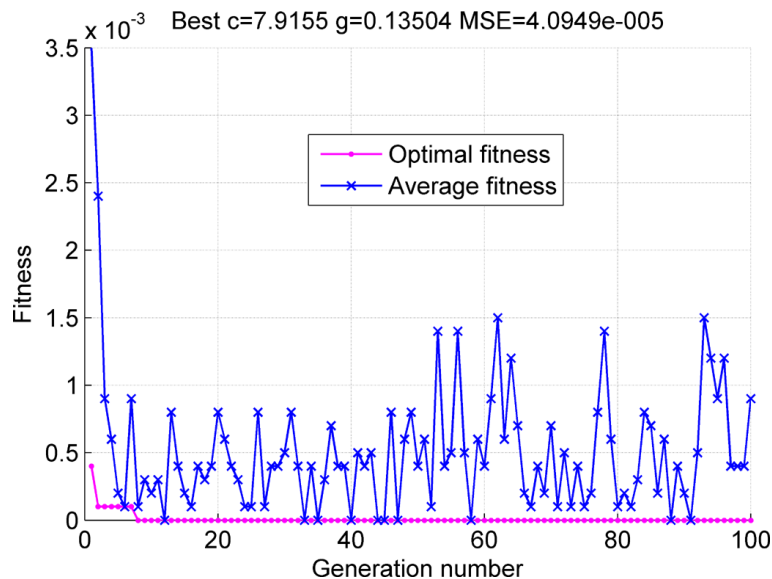


Fig. 6. The fitness curve of searching for the optimal parameters of the single-factor SVM by GA.

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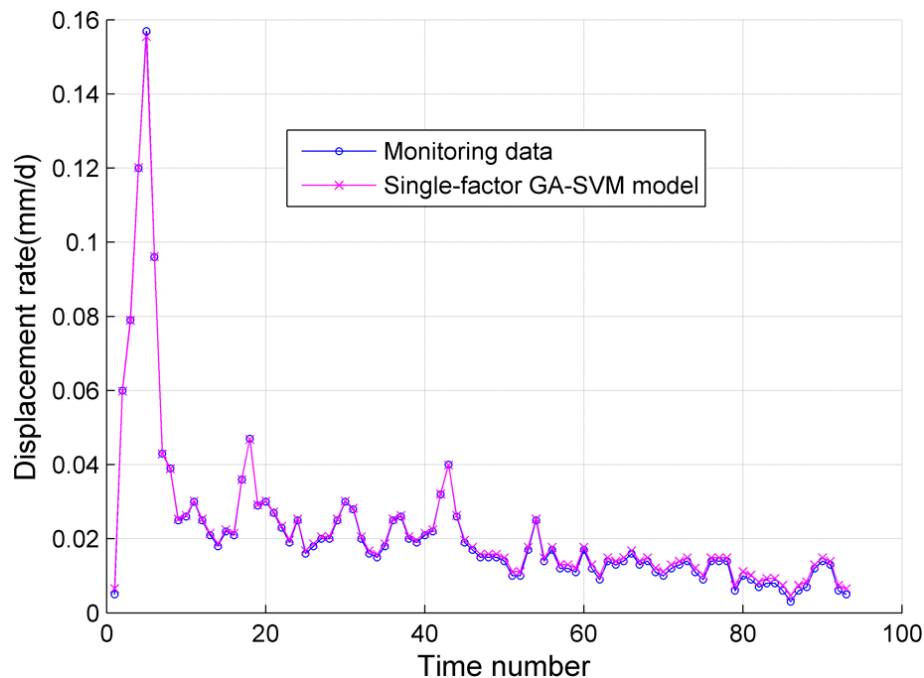


Fig. 7. The curves of the monitoring and predicting values of the displacement rate of the landslide with time.

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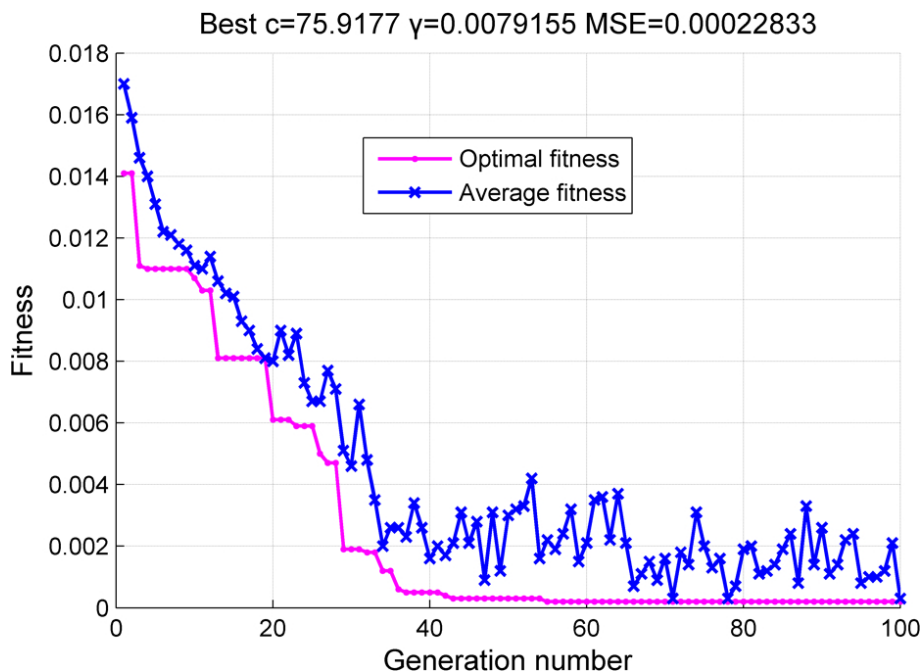


Fig. 8. The fitness curve of searching for the optimal parameters of the multi-factor SVM by GA.

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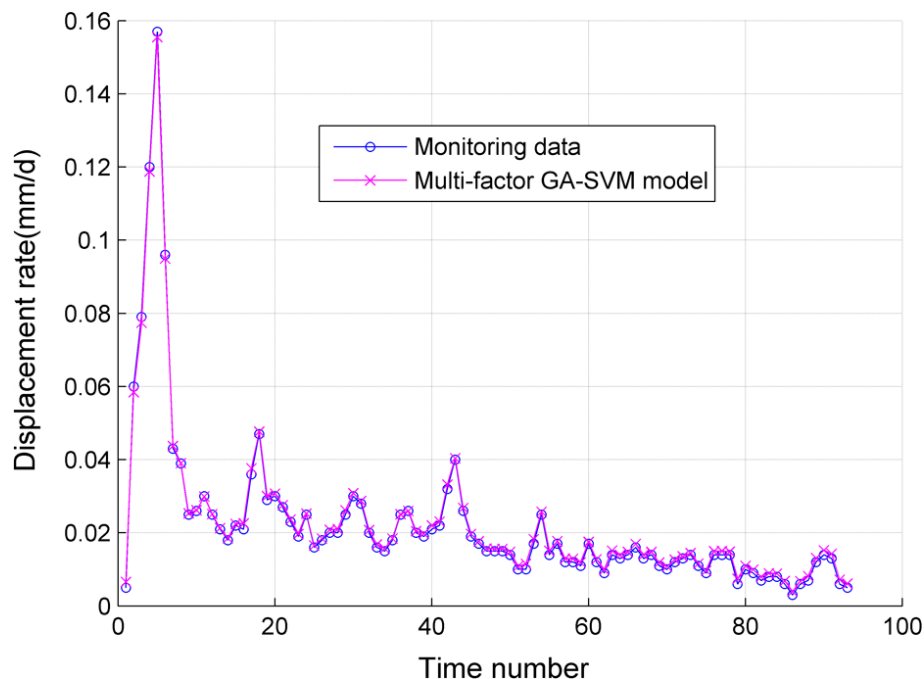


Fig. 9. The curves of the monitoring and predicting values of the displacement rate of the landslide with time.

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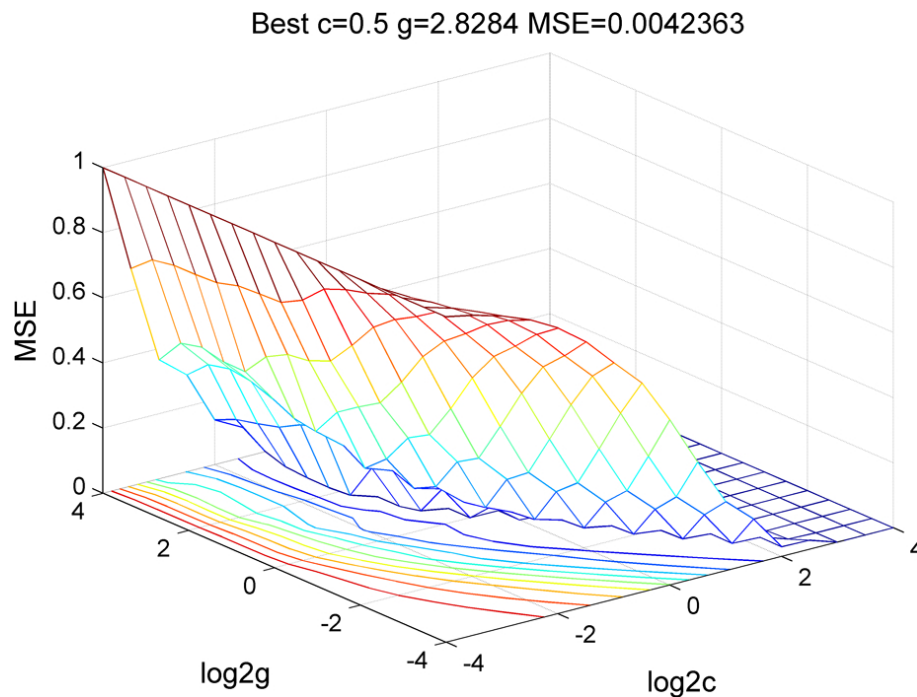


Fig. 10. The 3-D contour map of the parameters selection of the single-factor SVM model by using grid-search method.

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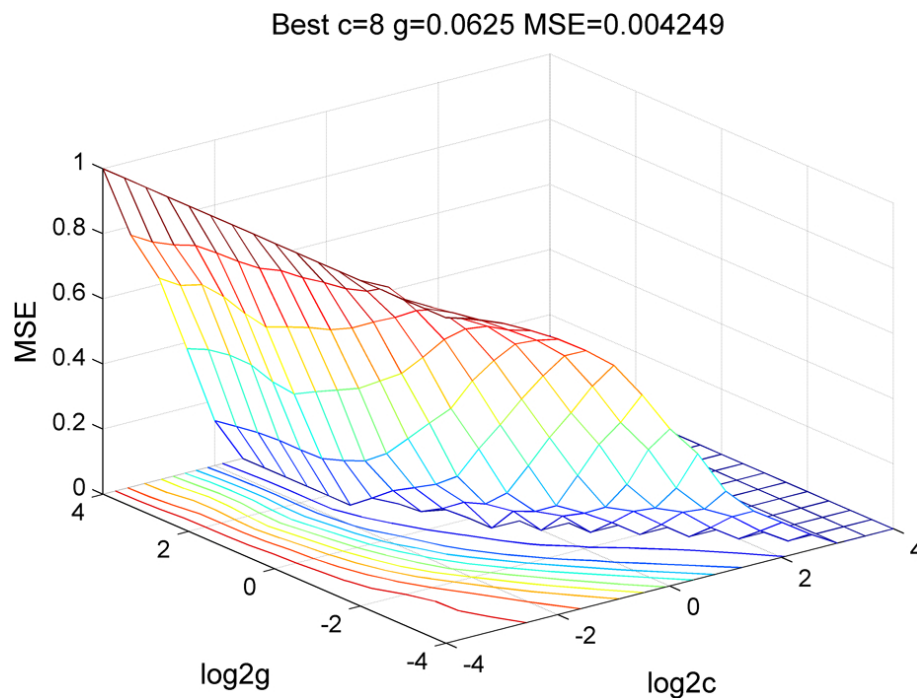


Fig. 11. The 3-D contour map of the parameters selection of the multi-factor SVM model by using grid-search method.