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Application of support vector machine to synthetic earthquake prediction*

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Abstract This paper introduces the method of support vector machine (SVM) into the field of synthetic earthquake prediction, which is a non-linear and complex seismogenic system. As an example, we apply this method to predict the largest annual magnitude for the North China area (30°E–42°E, 108°N–125°N) and the capital region (38°E–41.5°E, 114°N–120°N) on the basis of seismicity parameters and observed precursory data. The corresponding prediction rates for the North China area and the capital region are 64.1% and 75%, respectively, which shows that the method is feasible.

Key words: **support vector machine; seismicity parameter; precursory data; synthetic earthquake prediction**
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1 Introduction

The support vector machine (SVM) has not only a strict theory basis, but also a strong generalization (prediction) capacity, which can better solve the practical problems of small samples, nonlinearity, higher dimension and local minimum point. At present, SVM are widely used in text classification, handwriting recognition, image classification and bioinformatics, and now it has been extended to synthetic estimates and prediction of time series. Wang et al (2005, 2006) introduced the method to predict strong earthquakes in Chinese mainland and studied the non-linear relations between the time series of strong seismicity in China and the global large earthquakes as well as sunspot activities. His applications have obtained some meaningful results.

In view of that earthquake preparation-occurrence is a complex nonlinear dynamic process, we introduce SVM into a kind of synthetic earthquake prediction. The preliminary research by this method on the basis of seismic parameters has obtained a better result (Jiang et al, 2006). In this paper, SVM is used for a synthetic earthquake prediction in the North China area and the capital region on the basis of both seismicity parameters and observed precursory data.

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2 Basic principle of SVM regression algorithm (Vapnik, 1995)

It is firstly to consider the linear regression model. Suppose that a sample with k cases is described as

$$(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \cdots, (\boldsymbol{x}_k, y_k) \in \mathbf{R}^n \times \mathbf{R} \tag{1}$$

the linear discriminant function is

$$f(\boldsymbol{x}) = \boldsymbol{w} \bullet \boldsymbol{x} + b \tag{2}$$

and assume that all the training data can be fitted as a linear function without error under the accuracy of ε, that is,

$$\begin{cases} y_i - (\boldsymbol{w} \bullet \boldsymbol{x}_i + b) \le \varepsilon \\ (\boldsymbol{w} \bullet \boldsymbol{x}_i + b) - y_i \le \varepsilon \end{cases} \quad i = 1, 2, \cdots, k . \tag{3}$$

Considering the case of permissible fitting error, the relaxation indexes $\xi_i \ge 0$ and $\xi_i^* \ge 0$ are introduced. Then equation (3) turns into the following equation:

$$\begin{cases} y_i - (\boldsymbol{w} \bullet \boldsymbol{x}_i + b) \le \varepsilon + \xi_i \\ (\boldsymbol{w} \bullet \boldsymbol{x}_i + b) - y_i \le \varepsilon + \xi_i^* \end{cases} \quad i = 1, 2, \cdots, k, \tag{4}$$

where $\xi_i \ge 0$ and $\xi_i^* \ge 0$. That the SVM used for regression estimate is minimizing function (5) under constraints (4).

$$R(\boldsymbol{w},\xi,\xi^*)=\frac{1}{2}\boldsymbol{w}\bullet\boldsymbol{w}+C\sum_{i=1}^{k}(\xi_i+\xi_i^*) \quad (5)$$

The first term of equation (5) is to make the regression function more flat, so as to enhance the generalization ability. The second term is for reducing errors, the constant $C>0$ controls the punishment of samples whose errors are more than ε, where ε is a positive constant. If $|f(\boldsymbol{x}_i)-y_i|<\varepsilon$, then it will be ignored, otherwise, the error counted as $|f(\boldsymbol{x}_i)-y_i|-\varepsilon$.

With fewer samples, we generally use the dual theory to find a solution for SVMs and turn it into a quadratic programming problem. Then the Lagrangian function is introduced:

$$L(\boldsymbol{w},b,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*)=\frac{1}{2}\boldsymbol{w}\bullet\boldsymbol{w}+ C\sum_{i=1}^{k}(\xi_i+\xi_i^*)-\sum_{i=1}^{k}\alpha_i[\xi_i+\varepsilon-y_i+f(\boldsymbol{x}_i)]- \sum_{i=1}^{k}\alpha_i^*[\xi_i^*+\varepsilon+y_i-f(\boldsymbol{x}_i)]-\sum_{i=1}^{k}(\xi_i\gamma_i+\xi_i^*\gamma_i^*). \quad (6)$$

where, α_i, α_i^*, γ_i and γ_i^* (i=1, 2, ···, k) are not less than zero. Then the dual function of the Lagrange function (6) is

$$\widetilde{\omega}(\alpha,\alpha^*)_{\boldsymbol{w},b,\xi,\xi^*}=-\frac{1}{2}\sum_{i,j=1}^{k}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)(\boldsymbol{x}_i\bullet\boldsymbol{x}_j)- \sum_{i=1}^{k}(\alpha_i+\alpha_i^*)\varepsilon+\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)y_i. \quad (7)$$

The dual solution to this problem is maximizing equation (7) under constraints (8) (Xi, 1983)

$$\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)=0, \quad (8)$$

where $0\le\alpha_i\le C$ and $\le 0\le\alpha_i^*\le C$, and i=1, 2, ···, k.

The basic idea of non-linear approximation is: firstly, mapping the input space into the high-dimensional eigen-space by the non-linear transformation $\boldsymbol{\phi}(\boldsymbol{x})$; secondly, doing linear approximation in the high-dimensional eigenspace, that is $f(\boldsymbol{x})=\boldsymbol{w}\bullet\boldsymbol{\phi}(\boldsymbol{x})+b$; then obtaining the non-linear regression result in the original space. Thus the issue of non-linear regression is turned into maximizing function

$$\widetilde{\omega}(\alpha,\alpha^*)_{\boldsymbol{w},b,\xi,\xi^*}=-\frac{1}{2}\sum_{i,j=1}^{k}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\cdot [\boldsymbol{\phi}(\boldsymbol{x}_i)\bullet\boldsymbol{\phi}(\boldsymbol{x}_j)]-\sum_{i=1}^{k}(\alpha_i+\alpha_i^*)\varepsilon+\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)y_i \quad (9)$$

under constraints (8).

If $K(\boldsymbol{x}_i, \boldsymbol{x}_j)=\boldsymbol{\phi}(\boldsymbol{x}_i)\bullet\boldsymbol{\phi}(\boldsymbol{x}_j)$, then equation (9) is turned into

$$\widetilde{\omega}(\alpha,\alpha^*)_{\boldsymbol{w},b,\xi,\xi^*}=-\frac{1}{2}\sum_{i,j=1}^{k}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\cdot K(\boldsymbol{x}_i,\boldsymbol{x}_j)-\sum_{i=1}^{k}(\alpha_i+\alpha_i^*)\varepsilon+\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)y_i, \quad (10)$$

where

$$\boldsymbol{w}=\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)\boldsymbol{\phi}(\boldsymbol{x}_i). \quad (11)$$

Denoting $\boldsymbol{w}\bullet\boldsymbol{\phi}(\boldsymbol{x})=w_0$, $f(\boldsymbol{x})$ can be expressed as

$$f(\boldsymbol{x})=\sum_{i=1}^{k}(\alpha_i-\alpha_i^*)K(\boldsymbol{x}_i,\boldsymbol{x}_j)+b=w_0+b. \quad (12)$$

The theory of SVM uses the scalar product $K(\boldsymbol{x}_i, \boldsymbol{x}_j)=\boldsymbol{\phi}(\boldsymbol{x}_i)\bullet\boldsymbol{\phi}(\boldsymbol{x}_j)$ in the high-dimensional eigenspace rather than uses function $\boldsymbol{\phi}$ directly, thus the problem that w cannot be expressed with the unknown $\boldsymbol{\phi}$ is solved cleverly, where $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is called kernel function. It has been proved that a symmetric function can be a kernel as long as it meets the Mercer condition. The common kernel functions are: ① Polynomial kernel function $K(\boldsymbol{x}_i, \boldsymbol{x}_j)=(\boldsymbol{x}_i\bullet\boldsymbol{x}_j+c)^d$, $c>0$, d=1, 2, ···; ② Radial basis kernel function (RBF) $K(\boldsymbol{x}_i,\boldsymbol{x}_j)=\exp(-\|\boldsymbol{x}_i-\boldsymbol{x}_j\|^2/2\sigma^2)$; ③ Sigmoid kernel function $K(\boldsymbol{x}_i,\boldsymbol{x}_j)=\tanh[b(\boldsymbol{x}_i\bullet\boldsymbol{x}_j)+c]$.

It should be noted that these kernel functions have their own input ranges, which should be taken a data-scale transformation before specific applications. Selecting kernel function needs certain prior knowledge and there is no general conclusion at present. Scholkopf et al (1998) discussed the selection and construction of kernel functions.

According to the Karush-Kuhn-Tucker (KKT) conditions (Xi, 1983), at the optimal solution we have

$$\begin{cases}\alpha_i[\varepsilon+\xi_i-y_i+f(\boldsymbol{x}_i)]=0\\ \alpha_i^*[\varepsilon+\xi_i^*+y_i-f(\boldsymbol{x}_i)]=0\end{cases} \quad i=1,2,\cdots,k \quad (13)$$

and

$$\begin{cases}\xi_i\gamma_i=0\\ \xi_i^*\gamma_i^*=0\end{cases} \quad i=1,2,\cdots,k. \quad (14)$$

From equation (13) we have $\alpha_i\alpha_i^*=0$, and

$$\begin{cases}b=y_i-\varepsilon-\boldsymbol{w}\bullet\boldsymbol{\phi}(\boldsymbol{x}_i)\\ b=\varepsilon+y_i-\boldsymbol{w}\bullet\boldsymbol{\phi}(\boldsymbol{x}_i)\end{cases}. \quad (15)$$

The above-mentioned algorithms can be achieved easily by using the existing optimized software packages.

3 Application of SVM to synthetic earthquake prediction

According to the incomplete figures, dozens of seismicity parameters and precursors are used in monitoring and predicting earthquakes in China at present, such as hydrochemistry, water level, geoelectricity, geomagnetism, electromagnetic wave, crustal deformation, gravity, stress and so on. However, earthquake preparation is a non-linear and unstable process, accompanying a large number of different random phenomena. And seismicity parameters and earthquake precursors often show their single or group abnormal features in different forms. No matter in the synthetic earthquake prediction based on different groups of seismic precursory anomalies by the same method or based on the same group of seismic precursory anomalies by different methods, the conclusions drawn from different phases or the same phase of seismic activities are often inconsistent or even contradictory sometimes. It shows that there is an obvious non-linear relation between the precursory anomalies and the earthquake. The method of SVM maps the sample space into a high-dimensional eigenspace by a non-linear mapping ϕ, so as to solve the highly non-linear (classification) problems in the eigenspace. This is a major advantage of SVM for solving non-linear problems. Therefore, we apply in this paper the technology of SVM, which is usually used to solve the systematic problems of indeterminacy, non-linear and complexity, to predict the largest magnitude synthetically for a certain area during certain period on the basis of seismic precursory abnormal indexes (seismicity parameters and observed precursory data).

3.1 Selection of seismic precursory abnormal indexes

A large number of earthquake cases have shown that seismic precursory anomalies are discontinuous and diversified in spatial distribution. And the abnormal items, distribution and duration of seismic anomalies before various types of earthquakes differ greatly in different regions. However, in the short-term stage of earthquake preparation, the crust medium in the highly concentrative stress zone is almost in the state of instability. The short-term anomalies appeared in the unit time are more concentrative than the trend anomalies, and the occurrence of seismic precursory anomalies are quasi-synchronic in time. Therefore, we focus on the characteristics of tempo-spatial distribution of precursory anomalies prior to earthquakes in the North China area based on the analysis of 210 earthquake cases from *Earthquake Cases in China* (Zhang, 1988, 1990a, b, 1999, 2000; Chen, 2002a, b, c) and determine the following rules for selecting earthquake cases and seismic precursory abnormal indexes:

1) Earthquake cases with relatively concentrated seismic precursory anomalies in the observation items should be the first choice. The seismic precursory abnormal indexes of M5.0−5.9, M6.0−6.9 and $M\geq$7.0 earthquakes should make up 15%−20%, 30%−40% and ≥50% of the total observation items, respectively.

2) Seismic precursory anomalies relatively concentrated in a larger scope in the vicinity of epicentral region are selected. The seismic precursory anomalies of M5.0−5.9, M6.0−6.9 and $M\geq$7.0 earthquakes should locate within a radius of 200 km, 300 km and 500 km to the epicenters, respectively.

3) Single seismic precursory anomaly with a high-R score should be firstly selected. Similarly, the abnormal categories of A and B should be the first choice when the seismic precursory abnormal indexes have the same high-R score.

4) Relatively concentrated precursory anomalies should be selected on the basis of combining the anomaly registration form with the process map of abnormal duration of precursor observations and the accounted features of precursory anomalies, respectively.

The seismic precursory abnormal indexes in this paper are selected on the basis of the above-mentioned rules. And some of the earthquake cases are selected on the references of anomaly information of North China listed in the prediction research on the trend of Chinese earthquakes by the Center for Analysis and Prediction, China Earthquake Administration in the past years.

3.2 Construct of sample data set

The observed values of various types of seismic precursory anomalies are different in physical quantity and unit, so they cannot be compared directly or used as inputs for quantitative model. Therefore, in researching the evolutionary relationship between seismicity parameters, observed precursor anomalies and earthquake preparation-occurrence with time, we make a monthly statistic for the precursory abnormal durations before various types of earthquakes (Jiang et al, 2000), which are considered as predictors for the SVM synthetic prediction model. In Table 1, the abnormal durations of seismic gap, seismic belt, b-value, lack of earthquake, wave velocity ratio, electromagnetism, hydrochemistry, water level, tilt, and short leveling survey are taken as the synthetic predictors for the North China area. As different earthquakes have different abnormal indexes, so at least five or more abnormal indexes are required for each earthquake, otherwise, zero is assigned to the abnormal indexes. In this paper, the anomalous duration of each seismic abnormal index is taken as the input of SVM prediction model and its output is the predicted largest magnitude of future earthquake that might occur in a certain period and in a certain region.

Table 1 Statistics of precursory abnormal durations for the North China area (30°E–42°E, 108°N–125°N) (unit: mo)

No.	Earthquake			Abnormal duration										
	Date a-mo-d	Location	*M*	Gap	Belt	*b*	LOE	RWV	EM	Hyd	WL	Tilt	SL	AF
1	1966-03-22	Xingtai, Hebei province	7.2	0	0	0	0.9	0	0	0	1.6	0	12	6
2	1967-03-27	Hejian, Hebei province	6.3	0	0	0	0	0	0	0	0.3	0	0	6
3	1969-07-18	Bohai Sea	7.4	0	108	48	36	0	10	8	0	0	0	23
4	1973-12-31	Hejian, Hebei province	5.3	0	0	0	1	0	0.6	1	0	0	11	11
5	1974-04-22	Liyang, Jiangsu province	5.5	37	0	0	0	6	0	0	0.2	0	0	4
6	1975-02-04	Haicheng, Liaoning province	7.3	60	0	0	13	39	20	16	0	18	17	39
7	1975-09-02	Langjiasha, South Huanghai	5.3	45	20	0	0	0	0	0	0	0	0	4
8	1976-04-06	Horinger, Inner Mongolia	6.3	131	164	33	5	0	0.2	0	11	1	0	30
9	1976-07-28	Tangshan, Hebei province	7.8	55	37	39	60	24	35	12	25	0	13	74
10	1976-11-15	Ninghe, Tianjin	6.9	0	0	0	0	0	3	0.5	0.1	0	0	17
11	1977-05-12	Ninghe, Tianjin	6.3	0	0	0	0	0	1.2	0.3	0	0	0	6
12	1978-05-18	Yingkou, Liaoning province	5.9	33	3	33	0	19	2	4	1	4	3	15
13	1979-03-02	Guzhen, Jiangsu province	5.0	22	0	24	16	16	0	0	0	0.5	0	8
14	1979-06-19	Jiexiu, Shanxi province	5.2	29	0	49	0	0	0	0.2	0	0.2	6	10
15	1979-07-09	Liyang, Jiangsu province	6.0	36	0	60	24	24	0	14	0.3	0	12	32
16	1979-08-25	Wuyuan, Inner Mongolia	6.0	32	12	0	12	0	14	0	0.3	0	12	10
17	1981-08-13	Fengzhen, Inner Mongolia	5.8	0	12	0	12	0	5	0	0.3	0	0	8
18	1981-11-09	Longrao, Hebei province	5.8	0	10	0	0	0	10	6	0	1	0	14
19	1983-11-07	Heze, Shandong province	5.9	39	7	11	13	12	3	2	0	0	0	16
20	1984-05-21	South Huanghai Sea	6.2	108	8	72	0	0	13	24	0	47	9	37
21	1985-11-30	Renxian, Hebei province	5.3	0	0	0	0	0	0.6	0.5	0.1	0	0	5
22	1987-02-17	Sheyang, Jiangsu province	5.1	23	23	27	0	0	0	0	0	2	0	12
23	1989-10-19	Datong, Shanxi province	6.1	56	24	13	34	20	5	12	10	0	0	73
24	1990-02-10	Taicang, Jiangsu province	5.1	0	11	60	0	0	0	5	6	2	1	39
25	1991-01-29	Xinzhou, Shanxi province	5.1	0	0	11	11	0	6	24	2	9	8	19
26	1991-03-26	Datong, Shanxi province	5.8	14	0	0	3	0	7	29	328	191	10	27
27	1991-05-30	Tangshan, Hebei province	5.1	0	6	0	3	0	0	1	7	0	0	8
28	1992-01-23	South Huanghai Sea	5.3	0	0	23	23	32	12	0	0	1	0	21
29	1994-07-26	South Huanghai Sea	5.3	0	10	14	0	0	0	0	0	0	0	8
30	1995-09-20	Cangshan, Shandong province	5.2	0	0	0	0	6	7	0	0	2	7	13
31	1995-10-06	Tangshan, Hebei province	5.0	0	0	5	0	0	0	3	10	4	6	16
32	1996-05-03	Baotou, Inner Mongolia	6.4	0	7	15	0	0	26	0	0	16	0	11
33	1996-11-09	South Huanghai Sea	6.1	46	154	10	0	2	62	4	13	15	10	25
34	1997-07-28	South Huanghai Sea	5.1	26	0	0	0	0	0	5	0	0	0	7
35	1998-01-10	Zhangbei, Hebei province	6.2	24	36	0	0	3	19	31	15	0	1	50
36	1999-11-01	Datong, Shanxi province	5.6	42	22	0	0	0	11	0	0	0	0	21
37	1999-11-29	Haicheng, Liaoning province	5.4	0	20	0	0	0	6	12	11	8	0	18
38	2000-01-12	Xiuyan, Liaoning province	5.1	0	0	0	0	0	4	2	3	0	7	10
39	2006-07-04	Wen'an, Hebei province	5.1	5	5	0	66	0	3	2	2	0	3	12

Note: LOE, RWV, EM, Hyd, WL, SL and AF represent the lack of earthquake, ratio of wave velocity, electromagnetism, hydrochemistry, water level, short leveling and abnormal frequency, respectively.

3.3 Learning and training of SVM

Firstly, kernel function is selected. In the comparative analysis of polynomial kernel, radial basis kernel and sigmoid kernel functions, we found that the polynomial kernel function d=1 is more suitable for predicting $M_{\max}$, the largest magnitude of the earthquake that might occur in the North China area in a certain period. And then by testing various ε and C and by 2.8 s' learning and training, we have obtained four supporting vectors when $\varepsilon = 0.6707$ and $C\to\infty$. The $\alpha_i - \alpha_i^*$ value of each supporting vector and its corresponding sample number are shown in Table 2. The corresponding values of w_0 and b are 32.365 and 2.56, respectively.

3.4 Result analysis

By introducing the SVM method into the synthetic earthquake prediction, we make a statistic analysis on the precursory abnormal durations shown in Table 1 as an example in the North China area. The former 2/3 cases are taken as learning samples and the latter 1/3 cases as samples for extrapolation testing. The results are shown in Table 3.

It is apparent from the results in Table 3 that the corresponding rate for training prediction of earthquake strength is 0.69, the corresponding rate for extrapolative prediction is 0.50 and the total corresponding rate is 64.1%.

Table 2 Learning results of support vectors and $\alpha_i - \alpha_i^*$ values of training samples

Support vector	Number of samples	$\alpha_i - \alpha_i^*$
1	21	2 608
2	25	0.670 7
3	32	0.003
4	28	96 920

Table 3 Testing results of SVM synthetic prediction model for North China area

$M_{\max}$	Training results		Extrapolation results	
	Actual earthquakes	Correct predictions	Actual earthquakes	Correct predictions
5.0–5.9	17	14	7	4
6.0–6.9	8	5	3	1
≥7.0	4	1	0	0
Total	29	20	10	5

In order to test its effectiveness, SVM method is used to predict the largest annual magnitude $M_{\max}$ for the capital region (38°N–41.5°N, 114°E–120°E) on the basis of the anomaly information of the capital region presented in the prediction research on the trend of Chinese earthquakes and the trends of short-term earthquake tracking in the capital region compiled by the Center for Analysis and Prediction of China Earthquake Administration since 2000. The anomaly information listed in the consultation reports compiled by relevant provinces, municipalities and research institutes are also used for reference, which are provided by the China Earthquake Information Network. The monthly abnormal durations of seismic precursory indexes (seismic gap, seismic belt, *b*-value, lack of earthquake, electromagnetism, hydrochemistry, water level and tilt) are taken as the inputs of SVM prediction model and the output is the predicted annual largest magnitude of earthquake in the capital region, which are shown in Table 4. If the permissible error is $\Delta M_{\max} = \hat{M}_{\max} - M_{\max} = \pm 0.5$, the corresponding rate for the predicted results is 0.75.

Table 4 Testing results of SVM synthetic prediction model for the capital region

No.	a-mo-d	Location	$M_{\max}$	$\hat{M}_{\max}$	$\Delta M_{\max}$
1	2000-06-25	Douhe, Tangshan	4.4	4.7	0.3
2	2001-09-19	Bohai	4.7	4.9	0.2
3	2002-05-19	Ninghe, Tianjin	4.7	4.5	0.2
4	2003-04-24	Ninghe, Tianjin	4.3	4.9	0.6
5	2004-01-20	Luanxian, Hebei	5.0	5.1	0.1
6	2005-08-31	Yuxian, Hebei	4.0	4.5	0.5
7	2006-07-04	Wen'an, Hebei	5.5	5.0	–0.5
8	2007-07-04	Yuxian, Hebei	3.8	4.5	0.7
	Mean squared error				0.19

4 Discussion and conclusions

SVM is a hot topic in the fields of statistical theory learning and machine learning, which is now in a boom period. In the current study of earthquake prediction, the physical processes of earthquakes are not known clearly, so it is still a practical way to apply mathematical statistical methods to earthquake prediction. Therefore, we introduce the method of SVM into the synthetic analysis and prediction on the basis of seismicity parameters and earthquake precursors. Our main purpose is to explore a new way to predict earthquake synthetically.

At present, the synthetic earthquake prediction is to study the evolutionary relation between seismic precursory anomalies and processes of earthquake preparation-occurrence on the basis of various geophysical observation means. As different earthquakes have different seismogenic tectonic environments and different rupturing styles, their geophysical volumes observed before earthquakes are certainly very different (Chen et al, 2008). Therefore, the key point in the synthetic earthquake prediction is to distinguish seismic precursory abnormal features and extract effective seismic abnormal information.

Different geophysical observation means have different physical properties and their corresponding abnormal features before earthquakes are also different, so it is difficult to use them directly in the synthetic prediction of earthquakes. In studying the precursory abnormal features of seismicities in different periods in this paper, we take the seismic precursory abnormal durations as the inputs of synthetic prediction model. It not only reveals the relationship between earthquake occurrence and precursory abnormal duration, but also assigns the inputs an identical dimension and obtains a better prediction result. However, further study is still needed for the combination and coordination of multiple abnormal indexes in the processes of earthquake gestation and occurrence.

In predicting the category of the largest magnitude in a certain period for the North China area, we find that the training result of multi-classifier of SVM is not satisfactory, which is due to the complexity of earthquake gestation, small probability of earthquake occurrence and extremely difficult acquisition of sample data. Because the physical mechanism of earthquakes is not known very clearly, it is a studying orientation in the future to improve the algorithm of SVM multi-classifier to adapt to the prediction of earthquake magnitude for different periods and different regions.

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