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PSR-SVR Network Public Opinion Prediction Model

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Abstract
The accurate prediction of network public opinion trends has great significance to prevent the public safety threat of negative network public opinion, and in allusion to time-dependent nature and chaos characteristic, this paper has proposed network public opinion prediction model (PSR-SVR) combined with chaos theory and SVRM. Firstly, the chaotic characteristic of network of public opinion has been proved, and Takens theorem is used to determine time-series phase-space reconstruction delay time and embedding dimension of network public opinion using mutual information method and GP method. Finally, in the phase space, support vector regression (SVR) is used to establish network public opinion prediction models and prediction model and to conduct comparison experiments with other prediction models. The results show that compared to the comparative models, PSR-SVR has improved the prediction accuracy and reliability of network public opinion, and its forecasted results have some practical values.
Keywords: PHASE-SPACE RECONSTRUCTION, CHAOS THEORY, NETWORK PUBLIC OPINION, SUPPORT VECTOR MACHINE, PREDICTION MODEL

1. Introduction

Internet public opinion is an important part of social public opinion, and as opposed to the traditional news media, it's strongly interactive, and users are both receivers and message originators, so that dissemination of information on the network can be more timely and rapid. Negative Internet public opinion will pose a larger threat to public safety, thus analysis and modeling of changes in network public opinion can be conducted to forecast its development trend, which can help authorities develop the right strategy to guide public opinion, having crucial practical significance in maintaining social harmony and stability [1, 2]. The current prediction methods of network public opinion are mainly divided into two categories: based on linear prediction method and based on machine learning method. Linear prediction method include autoregressive (AR), moving average (MA), differentiated Autoregressive Integrated Moving Average (ARIMA), etc. [3-5], and it is simple, easy to implement. Especially ARIMA is highly flexible, and it can represent a variety of different types of time series models, combining the advantages of time-series analysis and regression analysis, the most widely used to predict changes in the network public opinion. However, ARIMA is a linear prediction model, and the changes in the network public opinion are affected by many factors. Being nonlinear, ARIMA cannot capture the nonlinear changing characteristics of network public opinion changes, which has affected the prediction accuracy [6]. Machine learning algorithms mainly include hidden Markov model (HMM), gray theory (GM), artificial neural networks (ANN), support vector regression (SVR), etc., and its modeling is based on the nonlinear theory, more accurately describing changes in network public opinion, and it is relatively traditional linear prediction model, with further improved prediction accuracy and more ideal results[7-10]. Since people are involved in the network public opinion, and users have their own preferences and ideas, network public opinion has strong chaos characteristic. The current machine learning algorithms ignore the chaotic nature of the network public opinion, thus the established model cannot describe the changes in network public opinion in a comprehensive and accurate manner, and the forecast accuracy should be further improved [11].

2. Phase-space Reconstruction and Chaotic Recognition of Network Public Opinion

Phase space reconstruction is the basis of chaos theory, and the main idea is that: The evolution of any component of the system is decided by the other components interact with it. The information of related component are hidden in the evolutionary process of this component, thus through analysis of time series of a certain component, we understand the dynamic characteristic of the original system, to extract and recover the law of the original system [12].

Assuming the time sequence is: x (t), t = 1,2, ..., N, and by selecting the appropriate embedding dimension m and the delay time τ, reconstruction can be made to get a multi-dimensional vector sequence X (t) to tap the information hidden in time series and to recovery the prime power system;

$$X(t)=\{x(t),x(t+\tau),\cdots,x[t+(m-1)\tau]\} \quad (1)$$

In the formula, M = N- (m-1) τ, and M is the number of phase points.

2.1. Sample Data and Preprocessing

“Baby theft on vehicle in Changchun” is selected as the source event of network public opinion, since Tianya community is the number one of “Top 100 Global Chinese Forums” jointly issued by PhoenixNet and iResearch Consulting Group, having advantages in visibility and influence and the data are representative, thus the forum data in Tianya is selected as the data source of network public opinion. A total of post numbers for 96 hours were collected as research objects from the source post of “baby theft on vehicle in Changchun” case at 10:00 am on March 4, 2013 till 10:00 am on March 8th, 2013, specifically shown in Figure 1.

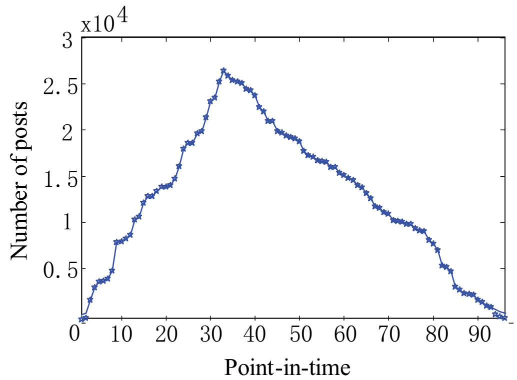

Figure 1. Collected data of network public opinion

Seen from Figure 1, the variation range of network public opinion is relatively large, in order to avoid data with wide range of values submerging data with small range of values; and the value of SVR kernel function depends on the inner product of the feature vector, and too large data would have adverse effects on the training process. Therefore, normalization processing is conducted before the data are input into SVR, and the normalization formula is:

$$x'=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \quad (2)$$

In the formula, x' represents the value after normalization; $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values respectively.

2.2. Phase Space Reconstruction of Internet Public Opinion

2.2.1. Computing Delay Time of Mutual Information

(1) Dimensional phase diagram of network public opinion measure time-series {x (t)} is constructed, and we set$(x,y)=[x(t),x(t+\tau)]$, τ = 1.

(2) We draw a rectangle frame in the two-dimensional phase diagram, and the rectangle frame is divided into equally spaced small grids. x0 and y0 are the starting point of the grids; Δx and Δy are the length of grids in x and y directions; Mx and My are the number of grids in x and y directions.

(3) If $x_0 \le x(i) \le x_0+\Delta x$, $y_0 \le y(j) \le j_0+\Delta y$, i, j = 1,2, ..., N, then the point $[x(i),y(j)]$ rests in the rectangle frame and satisfies $(k\text{-}1)\Delta x \le x(i)\text{-}x_0 \le k\Delta x$, $(l\text{-}1)\Delta y \le y(i) \le y(i)\text{-}y_0 < k\Delta y$, k=1,2,…,M, l=1,2,…,M, and the point $[x(i),y(j)]$ falls on the small grid of $\Delta_{k,j}$, recorded as once. All the points are searched, and the frequency of falling in the small grid of (k,l) is N_{xy}, while the point of falling into the small grid of k-1 to k is N_x, and the number falling into the small grid of l-1 to l is N_y. $p[x(i)]=N_x/N$, $p[y(i)]=N_y/N$, $p[x(i),y(i)]=N_{xy}/N$, and N are all sampling points, which are substituted into equation (3) to (5), and the mutual information function value I (x, y) with delay time of τ is figured out.

$$H(x) = -\sum_{i=1}^{q} P(x_i)\log P(x_i) \tag{3}$$

$$H(x,y) = -\sum_{i,j} P(x_i,y_i)\log P(x_i,y_i) \tag{4}$$

$$I(x,y) = H(X) + H(Y) - H(X,Y) \tag{5}$$

In formula, H (X) represents the uncertainty degree of X; $P(x_i)$ is the probability of occurrence of x_i; q is the total number of state; H (X, Y) is the co-entropy of X and Y, and P (x_i, y_i) is concurrent joint probability of event x_i and y_i.

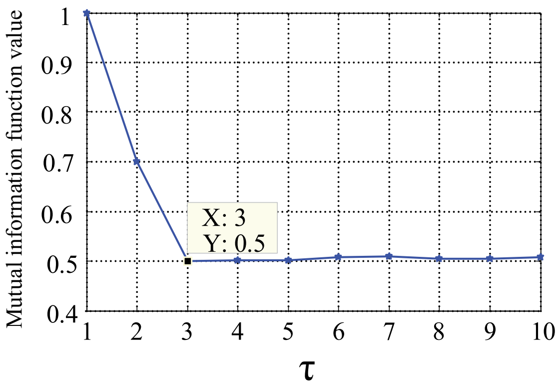

Figure 2. Delay time computing of network public opinion

(4) We set τ = τ + 1, return to step (2).

Mutual information function changing curve of network public opinion time-series is shown in Figure 2. As can be seen from Figure 2, when τ = 3, the mutual information function reaches the first minimal value, so the time series of network public opinion is τ = 3.

2.2.2. Embedding Dimension Selection Using G-P Method

(1) According to the mutual information, we obtain τ = 3, and the initial value of embedding dimension is m = 1.

(2) The proper critical distance r is selected, and on the basis of the equation (6), C_n (r) is calculated, and vector distance is calculated using ∞ norm, and that is, the largest differential component of the two vectors is taken as vector distance.

$$C_n(r) = \frac{1}{M^2}\sum_{i,j=1}^{M}\theta\left[r - \left\|X(i) - X(j)\right\|\right] \tag{6}$$

In the formula, M is the number of phase points; r is the critical distance; θ is unit function of Heaviside.

(3) Line segment in logC (r) n ~log$r$ curve is fitted using the least squares, and the slope of the straight line is correlation dimension D.

(4) The embedding dimension is increased, namely m = m +1, and we return to step (2).

Internet public opinion time-series correlation dimensions in different embedded dimensions are as shown in FIG. From Fig. 3, when the embedding dimension is m = 5, the correlation dimension is saturated, which indicates that the optimal time series of network public opinion is m = 5.

2.3. Chaotic Recognition of Network Public Opinion Time-series

Chaotic system is sensitive to initial values, and if the maximum Lyapunov exponent of system is λ1> 0, then the system must be chaotic. Based on small-data

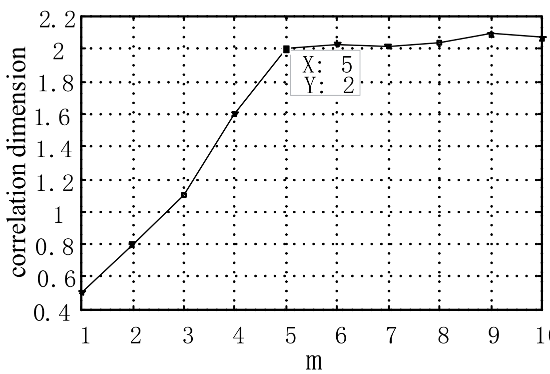

Figure 3. Embedding dimension of network public opinion calculating correlation dimension

method, the maximum Lyapunov index is calculated as follows:

(1) Perform rapid Fourier transformation of the time series x (t), t = 1, 2, ..., N, to calculate the average period p.

(2) Calculate delay time τ using mutual information method.

(3) Reconstruct phase space X (t), t = 1, 2, ..., M on the basis of delay time τ and embedding dimension m

(4) Find the nearest neighbor $X(\hat{t})$ of each point X (t) in the phase space, and limit short-term separation, namely

$$d_t(0) = \min_{\hat{t}} \left\| X(t) - X(\hat{t}) \right\|, \left| t - \hat{t} \right| > p \quad (7)$$

In which t=1,2,…,M

(5) For each point X (t) in the phase space, calculate the distance d_t(i) behind the neighborhood point to the i-th discrete time steps.

$$d_t(i) = \left\| X(t+i) - X(\hat{t}+i) \right\|, i = 1, 2, \cdots, \min(M-t, M-\hat{t}) \quad (8)$$

(6) Determine the average x (i) of the Ind_t (i) of all t for each i, namely

$$x(i) = \frac{1}{q\Delta t} \sum_{j=1}^{q} Ind_j(i) \quad (9)$$

In the formula, q is the number of non-zero d_t (i), and the regression line is drawn with the least squares method, and the slope of the line is the largest Lyapunov exponent.

By computation, it is obtained that the average cycle p = 1, the embedding dimension m = 5, the delay time τ = 3 of network public opinion time-series, and by least squares fitting straight-line, the slope is the largest Lyapunov exponent, getting λmax = 0.00152> 0, which shows that the network public opinion time-series has a weak chaotic nature.

2.4. Support Vector Machine Method

2.4.1. Support Vector Machine Regression

Support vector machine is a machine learning algorithm based on statistical learning theory, seeking the best compromise between the complexities of the model and learning ability, in order to obtain the best generalization ability [13]. Regression estimation function of SVR is

$$f(x) = w \cdot \varphi(x) + b \quad (10)$$

In the formula, w stands for weight vector, and b indicates bias vector.

Make the expected risk prediction function minimized:

$$\min J = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i^* + \xi_i) \quad (11)$$

Constraints are:

$$\begin{cases} y_i - w\cdot\varphi(x) - b \le \varepsilon + \xi_i \\ w\cdot\varphi(x) + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, n \end{cases} \quad (12)$$

Among them, ξ_i, ξ_i^* is the relaxation factor, and C represents penalty factor.

By introducing Lagrange multiplier, the above-mentioned optimization problem becomes a typical convex quadratic optimization, namely

$$L(w,b,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*) = \frac{1}{2}\|w\| + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$
$$-\sum_{i=1}^{n}\alpha_i(\xi_i + \varepsilon - y_i + f(x_i)) - \sum_{i=1}^{n}\alpha_i^*(\xi_i^* + \varepsilon - y_i + f(x_i)) \quad (13)$$
$$-\sum_{i=1}^{n}(\xi_i\gamma_i - \xi_i^*\gamma_i^*)$$

Among them, α_i and α_i^* represent Lagrange multipliers.

To speed up the solving rate, the formula (11) is converted into paired dual form, that is

$$W(\alpha,\alpha^*) = -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(\varphi(x_i),$$
$$\varphi(x_j)) + \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)y_i - \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\varepsilon \quad (14)$$

Constraints are:

$$\begin{cases} w = \sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)x_i \\ \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i, \alpha_i^* \le C \end{cases} \quad (15)$$

When solving practical problems, we just need to use support vector to solve, and then the regression estimation function is

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(\varphi(x_i), \varphi(x)) + b \quad (16)$$

Instead of using $(\varphi(x_i), \varphi(x))$, the kernel function $k(x_i, x)$ can avoid the curse of dimensionality, then:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x) + b \quad (17)$$

This paper chooses radial basis function as kernel function of SVR, and final regression function of SVR is:

$$f(x)=\sum_{i=1}^{N}\alpha_i \exp\left(-\frac{\left\|x_i-x_j\right\|^2}{2\sigma^2}\right)+b \quad (18)$$

In the formula, σ is the width of the radial basis kernel function.

2.4.2. SVR Network Public Opinion Prediction Model

The data set D = {x (t), t = 1, 2, ..., N} of network public opinion time series is given, taking the delay time τ = 3, embedding dimension m = 5, and according to the above method of phase space reconstruction, we can get the data set in the spatial domain: $D=\{X(t),Y(t)\},t=1,2,\cdots,M$. Among it, $X(t)=\{x(t),x(t+\tau),\cdots,x[t+(m-1)\tau]\}$, $Y(t)=x(t+1+(m-1)\tau)$ t = 1,2, ..., M, written in matrix form as:

$$X=\begin{pmatrix} x(1) & x(1+\tau) & \cdots & x(1+(m-1)\tau) \\ x(2) & x(2+\tau) & \cdots & x(2+(m-1)\tau) \\ \vdots & \vdots & \vdots & \vdots \\ x(M) & x(M+\tau) & \cdots & x(M+(m-1)\tau) \end{pmatrix} \quad (19)$$

$$Y=\begin{pmatrix} x(2+(m-1)\tau) \\ x(3+(m-1)\tau) \\ \vdots \\ x(M+1+(m-1)\tau) \end{pmatrix} \quad (20)$$

Prediction model in phase space domain is to use the point X (t) in phase space to predict Y (t), that is, to find a mapping function F, so as to

$$Y(t)=F(X(t)) \quad (21)$$

This paper calculates the mapping function through the use of SVR, and PSR-SVR-based modeling process is shown in Figure 4.

3. Prediction Experiment

3.1. Simulation Environment

In environment of PIV 3.0G CPU, 2G RAM, the operating system of Windows 2000, the algorithm is achieved by VC++ programming. Using ARIMA, SVR (no phase space reconstruction), PSR-BPNN is used as a comparison model, RMSE and MPAE used as the evaluation criteria of strength and weakness of the model. They are defined as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t-\hat{x}_t)^2} \quad (22)$$

$$MAPE=\frac{\sum_{t=1}^{n}\left|(x_t-\hat{x}_t)/x_t\right|}{n}\times 100 \quad (23)$$

In the formula, x_t and $\hat{x}_t$ are actual and predicted values respectively and n is the number of samples.

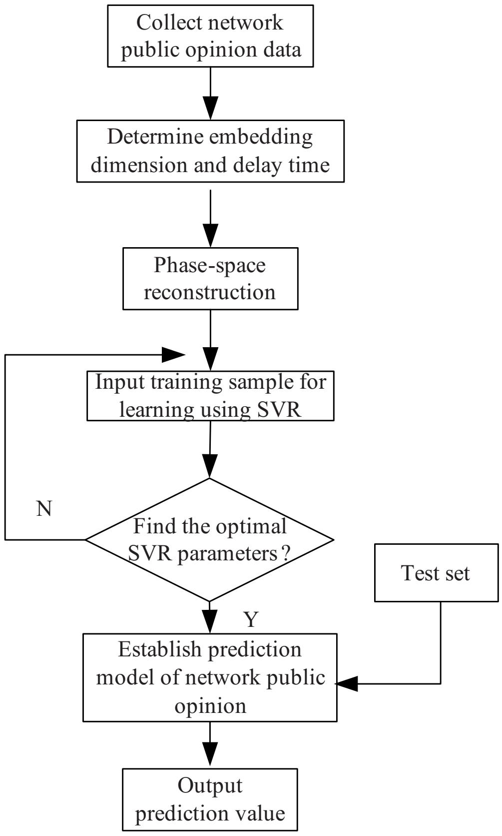

Figure 4. Forecasting process of PSR-SVR network public opinion

3.2. Result and Analysis

3.2.1. One-step Prediction

Since the original training sample is 65, and the optimal embedding dimension is m = 5, then the reconstructed new training set is 66-5 = 61. Firstly, training is conducted for 61 containing data for one-step prediction and the true value of the forecasting point is added to the training set, then for one-step prediction and so on. Finally, we get one-step predictive value of 30 test sets, and then the final prediction value is compared with the real value of test set, and the corresponding RMSE and MAPE are calculated. BP neural network structure is 5-11-1; by PSO algorithm, the obtained SVR optimal value is C = 100, σ = 1.715, and ARIMA (3, 2, 2) is selected for ARIMA model. Forecasted results of network public opinion test set for each model are shown in Figure 5, their respective RMSE and MAPE as shown in Table 1.

Table 1. Comparison of one-step prediction performance for each model

Model	*RMSE*	*MAPE*
ARIMA	468.274	14.05%
PSR-BPNN	400.997	11.71%
SVR	350.187	6.58%
PSR-SVR	184.501	1.96%

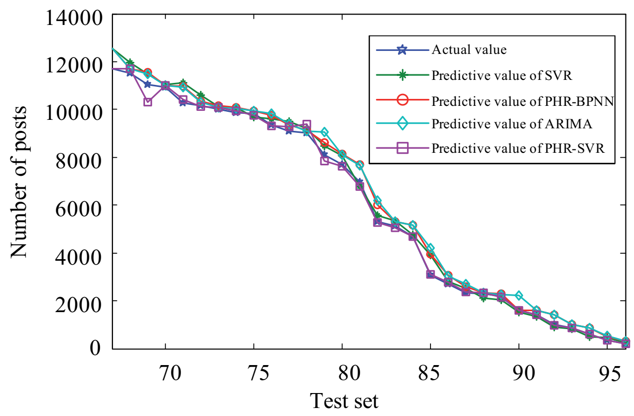

Figure 5. One-step forecasted results of network public opinion

Analyzed from the results in Table 1 and Figure 5, we can get the following conclusions:

(1) Compared to the ARIMA, PSR-SVR network public opinion has substantial increase in prediction accuracy, which is mainly because the ARIMA cannot capture the nonlinear changing characteristics of the network of public opinion time-series, while PSR-SVR's use of SVR nonlinear prediction ability has effectively improved the prediction accuracy of the network of public opinion.

(2) Compared to the SVR, PSR-SVR network public opinion has smaller prediction error value, the predicted value very close to the real value, which is mainly because the PSR-SVR mines information implicit in network public opinion time-series by using PSR, able to describe the variation tendency of network public opinion in a more accurate and comprehensive manner, to obtain more reliable predictions, which has further improved the prediction accuracy of network public opinion.

(3) Compared to the PSR-BPNN, PSR-SVR always has relatively stable forecasted results, and the predicted RMSE and MAPE values are far less than those of the PSR-BPNN, which is mainly because the SVR has overcome the problems of BPNN overfitting, local minima and difficulty in determining network parameters very well, with stronger generalization and higher forecast accuracy.

3.2.2. Multistep Prediction

Internet public opinion predicted time generally requires a large amount initial lead. The use of one-step prediction (i.e. only the network public opinion in next hour of the current time can be predicted) can neither effectively reflect the trend of s network public opinion, nor make effective and timely response to some of the negative network public opinion. Therefore, it is necessary to extend one-step prediction to multi-step prediction, and then the multi-step prediction method is used to predict the network public opinion in the next 24 hours. Comparison between real values and the predicted values for each model is shown in Figure 6, their RMSE and MAPE as shown in Table 2.

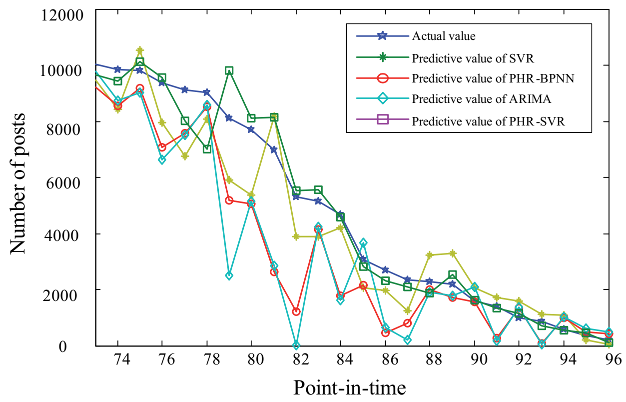

Figure 6. Comparison of pre-forecasted results using multistep prediction method

Table 2. Comparison of multistep prediction performance for each model

Prediction Model	*RMSE*	*MAPE*
ARIMA	2216.429	39.61%
PSR-BPNN	1848.875	32.19%
SVR	1169.536	21.62%
PSR-SVR	680.8821	9.00%

Fig. 6 and Table 2 show that multi-step prediction of ARIMA, SVR, PSR-BPNN network public opinion is less accurate, with quite great error, unreliable predictions, and lower practical value of forecasted results, while PSR-SVR prediction error is significantly less than the comparison model, and PSR-SVR can predict trends of network public opinion variation more accurately, superior to the comparison model in forecast performance, and the predicted results have great practical value.

3.2.3. Prediction of Other Popular Topics on Internet

In order to make the performance of model more convincing, testing experiments are conducted for the most popular topics in April 2103 such as "the exposure of PLA new military vehicle license plate", "Apple's apology to Chinese consumers", "US media's declaration of the China's deploying troops to the border of China and North Korea," "forfeited sister's Chinese style of crossing roads in Zhejiang and chasing after police and spitting", "Japan's permission of Taiwan fishers fishing in the Diaoyu Islands", "Liu Zhijun's exposed bribery of 60 million dollars", and the obtained one-step prediction errors are shown in Table 3. From Table 3, PSR-SVR get better prediction accuracy, and the prediction error is controlled within effective range (5%), and the results show that PSR-SVR is a predictive model of network public opinion with high prediction precision and good versatility.

Table 3. One-step prediction error of PSR-SVR for other popular topics on Internet

No.	Hot topics
1	the exposure of PLA new military vehicle license plate
2	Apple's apology to Chinese consumers
3	US media' declaration of the China's deploying troops to the border of China and North Korea
4	Forfeited sister's Chinese style of crossing roads in Zhejiang
5	Fishing in the Diaoyu Islands
6	Liu Zhijun's bribery

No.	*RMSE*	*MAPE*
1	113.98	2.37%
2	153.17	2.16%
3	133.43	1.89%
4	142.65	1.76%
5	159.08	2.45%
6	150.88	2.13%

Conclusions

Network public opinion is comprehensively influenced by a variety of factors, time-varying and chaotic, a complex changing system, as well as the accurate predictive model difficult to be established by traditional forecasting algorithms. On account of chaotic changing characteristics of network public opinion, a network public opinion based on PSR-SVR is established using chaos theory and SVR. The results show that: compared to the comparison model, PSR-SVR has improved prediction accuracy of network public opinion, having more stable forecasted results, more accurately describing the complex trends of network public opinion. Therefore, the forecasted results help correctly grasp the development of the network public opinion, thereby contributing to scientific and rational guidance and management of a variety of network communication platforms, and promoting the implementation of harmonious society building.

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The Old and New Notes Recognition Algorithm Based on Image Edge Character

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Abstract
The classification accuracy of the existing notes feature recognition based on image processing technology is widespread poor, it's vulnerable to the restriction from external conditions. Aiming at the defect, the denomination recognition method about note image is improved. And the notes image pre-processing include two parts of