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Introducing atmospheric angular momentum into prediction of length of day change by generalized regression neural network model

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Abstract: The general regression neural network (GRNN) model was proposed to model and predict the length of day (LOD) change, which has very complicated time-varying characteristics. Meanwhile, considering that the axial atmospheric angular momentum (AAM) function is tightly correlated with the LOD changes, it was introduced into the GRNN prediction model to further improve the accuracy of prediction. Experiments with the observational data of LOD changes show that the prediction accuracy of the GRNN model is 6.1% higher than that of BP network, and after introducing AAM function, the improvement of prediction accuracy further increases to 14.7%. The results show that the GRNN with AAM function is an effective prediction method for LOD changes.

Key words: general regression neural network (GRNN); length of day; atmospheric angular momentum (AAM) function; prediction

1 Introduction

Earth rotation is affected by the interactions of solid Earth with the atmosphere, ocean, mantle and core [1−3]. Earth rotation includes polar motion and length of day (LOD) changes, which are called the earth rotation parameters (ERPs) in geodesy or astronomy [2]. Accurate ERPs are required in the transformation between the earth and the celestial reference frame, and also play important roles in modern space navigations, explorations and military applications. The ERPs can be derived with modern high-precision space-geodetic techniques, such as very long base interferometry (VLBI), satellite laser ranging (SLR) and global positioning system (GPS). However, the complexity and time consuming in data processing always lead to time delay, which does not satisfy the real-time requirement for ERP in the transformation between the earth and the celestial reference frame, modern space navigations and explorations. Therefore, the prediction of ERPs from itself or combining with the atmosphere and ocean data is of great scientific and practical importance [4−5]. LOD is main part of ERPs, and thus the prediction of LOD is very important.

The predictions of LOD changes have been extensively investigated and a number of models have been developed. These models can be classified into two categories, linear and non-linear models. The linear models include the least-squares extrapolation (LS) [6], autocovariance model (AC) [7], and Kalman filter [8], etc. The non-linear models are mainly the artificial neural networks (ANN) [9]. LOD exhibits complicated time-varying characteristics, and the prediction given by the linear models is usually far from satisfactory, while the prediction by the non-linear ANN models seems to approach the LOD change. However, the BP artificial neural network put forward by SCHUH et al [9] has the problem of low efficiency, being sensitive to the initial values and non-unique solutions.

In this work, we propose to use a highly efficient ANN model, i.e., the generalized regression neural network (GRNN), to predict the time-varying behaviors of the LOD change. The GRNN was proposed after the BP ANN model, and is a kind of radial basis function (RBF) ANN [10]. It has good performance of local approximation and does not fall into the local minimum. No iteration is required in its training, and only one parameter needs to be adjusted, i.e. the smoothing factor. Therefore, the GRNN needs less computation time. Compared with the BP network, it requires a much smaller training sample, and has only three layers with a simple structure, which is suitable for solving the problems of approximation, prediction and classification. This method can overcome the shortcomings of the BP network, i.e., easily falling into the local minimum and time-consuming [10−14].

To improve the prediction accuracy of LOD change,

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the prediction method is investigated by introducing the atmospheric angular momentum (AAM) function that tightly correlates the LOD change to the GRNN model. As the solid Earth and its surrounding fluid layers form an approximately close dynamic system, changes of atmospheric or oceanic angular momentum will result in variations in the solid Earth's rotation, based on the conservation law of angular momentum [1, 3]. The variation of the earth rotation parameter is tightly correlated with the change of the AAM, and the AAM can be derived with the dynamic model of the atmosphere. WANG et al [15] found that the prediction accuracy is significantly improved after introducing the AMM to the BP network. In this work, the GRNN model is adopted to include the data of the axial AAM function for the prediction of LOD change, which is expected to further improve the prediction accuracy.

2 Prediction method

2.1 Data pre-processing

The data of the LOD change used in this work are taken from EOP 05C04 series of the IERS, with one data point per day spanning from 1980 to 2010. The data contain periodic changes with periods of 5 days to 18.6 years caused by the 62 zonal Earth tides. We first removed the contributions of the tides from the LOD changes using periodic models [16], and the residual series thus obtained are called as LOD residues (LODR) for simplicity hereinafter. All the predictions carried out are based on the data of LODR.

2.2 Introducing AAM to LOD prediction by GRNN

2.2.1 Detrend of LODR

The LODR, i.e., the LOD after removing the effects of tides, still includes some periodic changes, such as the annual and semi-annual terms [1]. These are trend terms that must be removed before further modeling. They can be approximate by LS method:

$$R(t)=At^2+Bt+C+D_1\sin\left(\frac{2\pi t}{P_1}\right)+D_2\cos\left(\frac{2\pi t}{P_1}\right)+ E_1\sin\left(\frac{2\pi t}{P_2}\right)+E_2\cos\left(\frac{2\pi t}{P_2}\right)+F_1\sin\left(\frac{2\pi t}{P_3}\right)+ F_2\cos\left(\frac{2\pi t}{P_3}\right) \quad (1)$$

where A, B and C are the parameters of mid/long-term trend, D_1 and D_2 are the parameters of annual term, E_1 and E_2 are the parameters of the semi-annual term in the LODR series, F_1 and F_2 are those for the 1/3-year term, and P_1=1, V P_2=1/2, and P_3=1/3.

These parameters can be determined with the least-square method and the LODR series. Then, the trend terms and the differences between the trend terms and LODR can be obtained. These differences are the LODR residual series. Subsequent modeling and prediction are based on the LODR residual series. The final prediction of LODR is the summation of the prediction of LODR residual series and the extrapolated trend terms. In Fig. 1, the original and extracted series of LOD are plotted as functions of time (from Jan. 1, 1980 to Dec. 31, 2010). From top to bottom, the data series are LOD, tides terms, trend terms, and detrended LODR (i.e., LODR residual series), respectively.

2.2.2 Detrend of AAM series χ_3

Of the components of the AAM function, the axial component χ_3 is strongly correlated with the LOD change. Thus, it is introduced into the prediction. The series of χ_3 is from the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR). The length of χ_3 is the same as that of the LOD. The linear and periodic trend terms of χ_3 are also approximated by LS fitting, and then its residual series is used for subsequent modeling.

2.2.3 LODR prediction by GRNN

The GRNN is a kind of modified RBF neural network model. It is a forward feedback neural network based on the non-linear regression theory. It consists of three layers, i.e. the input, the hidden and the output layer (see Fig. 2) [10−12]. The first layer of the network is the input layer, and $\boldsymbol{P}$ is the input vector with R dimensions. There are Q neurons in each layer. The input vector $\boldsymbol{P}$ is the residual series of the LODR. The number of neurons Q is determined by the input mode. The input adopted in this work is

$$C(t-qi),\ \cdots,\ C(t-3i),\ C(t-2i),\ C(t-1i),\ \chi_3(t) \quad (i=1,\ 2,\ 3,\ \cdots) \quad (2)$$

where t denotes the epoch of prediction, and i represents the time interval of input series. The input here is the q LODR residual series, so the number of neurons is Q=q.

The second layer of the network is the radial-basis hidden layer, and the number of neurons is equal to that of the training sample members. The weight function of this layer is the Euclidean distance function (expressed by distance $L_{1,1}$), which is the distance between the input of the network and the weight of the first layer. b^1 is the threshold of the hidden layer. The transfer function of the hidden layer is the RBF, which generally employs the Gaussian function:

$$R_i(x)=\exp\left(\frac{\left\|x-c^2\right\|}{2\sigma_i^2}\right) \quad (3)$$

where σ_i is the smoothing factor which is the only parameter needed to be adjusted, and the radial basis function becomes smooth with the increase of σ_i.

The third layer of the network is the output layer.

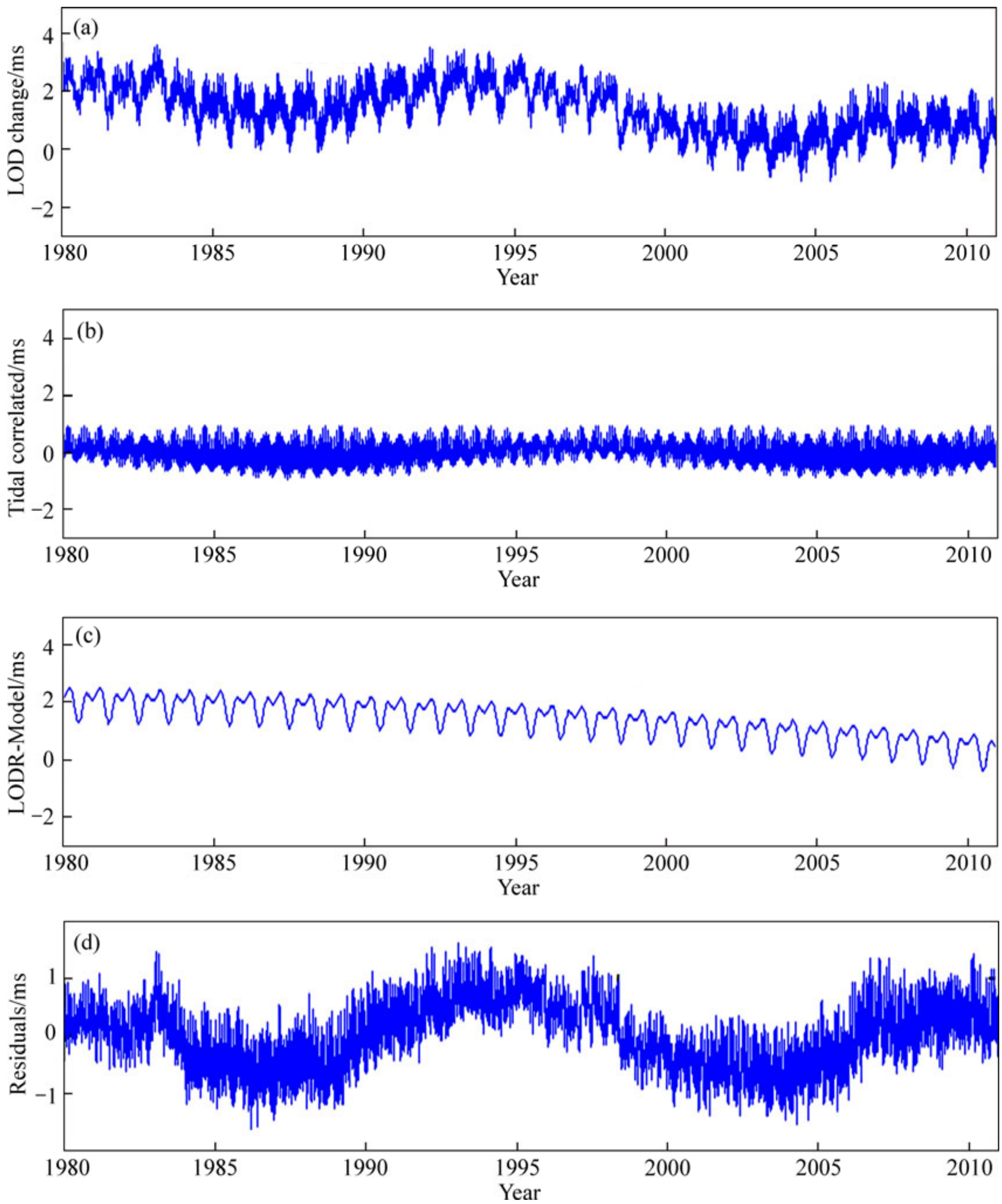

Fig. 1 LOD data (a), tidal terms (b), LODR trend data (model-fitted) (c) and detrended LODR residuals (d)

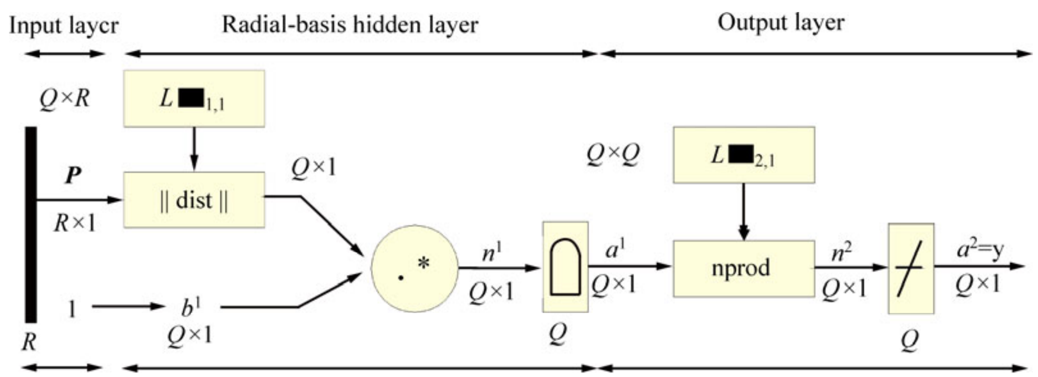

Fig. 2 Structure of GRNN

The weight function “npord” is the normalized dot product function. The transfer function is a linear function. It uses the results obtained by the weight function to compute the final output of the network. The final output of the network is then the prediction of LODR residuals. By adding the LODR trend series extrapolated by Eq. (1), one can get the final prediction of LODR.

2.2.4 Introducing χ_3 to LODR prediction by GRNN

Based on the prediction using the LODR residual series only, the AAM χ_3 component is introduced and jointly used with the LODR residual series to predict the LODR with the GRNN model. In the modeling, the χ_3 residual series is used as a neuron of the input layer to join the prediction. The training of the network is the same as that of LODR, and the only difference is both the LODR and χ_3 are used as input. So, in the input layer, the input vector $\boldsymbol{P}$ includes the LODR and the χ_3 residual series as well. The input model adopted is thus

$$C(t-qi),\ \cdots,\ C(t-3i),\ C(t-2i),\ C(t-1i),\ \chi_3(t)\quad (i=1,\ 2,\ 3,\ \cdots) \tag{4}$$

where t denotes the epoch of prediction, and i represents the time interval of input series. The first q inputs here are the LODR residual series and the final input is the χ_3 residual series at epoch t, so the number of neurons in the input layer is $Q=q+1$.

Through the radial-basis hidden layer and the output layer, the final output is the prediction of LODR residuals. Similarly, by adding the LODR trend series extrapolated by Eq. (1), one can get the final prediction of LODR. Figure 3 shows the flow chart of introducing AAM to the LODR prediction by GRNN.

2.3 Performance evaluation

To evaluate the performance of the proposed model, the mean absolute error (MAE) is adopted as the criterion:

$$E_i=\frac{1}{N}\sum_{j=1}^{N}\left|p_i^j-o_i^j\right| \tag{5}$$

where p^j is the output of the network (i.e., the predicted values) at epoch j; o^j is the LODR observational series at epoch j; i represents the time interval of input series; N is total number of predictions.

3 Experiment

In this work, we use the data of LOD change and the AAM function χ_3 with the time coverage between Jan. 1, 1980 and Feb. 28, 2008 to conduct experiment. The data in the period from Jan. 1, 1980 to Sep. 30, 2005 are used for modeling, and those in the period from Oct. 1, 2005 to Feb. 28, 2008 are used for model validation.

For simplicity, we refer the prediction model by GRNN with the AAM χ_3 as GRNN+AAM. To demonstrate the advantages of the GRNN model, the traditional BP network is also applied in this experiment. We employ the GRNN, GRNN+AAM, and the BP network to predict the LOD change of time span of 1, 2, ⋯, 390 days. The MAEs of the predictions by the three models are calculated and listed in Table 1.

From Table 1, the prediction accuracy of the GRNN model is higher than that of BP model except the prediction length of 1, 22, 26, 270 and 360 days. In terms of the prediction efficiency, however, the calculating time of the GRNN method is only around one tenth of that of BP model. From Fig. 4, we can see that the curve of GRNN prediction error is much smooth and the prediction error increases gradually with the increasing of the prediction length. In contrast, the prediction error of BP model is not stable with obvious jumping, which is the direct reason that the accuracy of the GRNN model is lower than that of BP model in 1, 22, 26, 270 and 360 days.

By comparing the GRNN＋AAM with the BP model, the prediction accuracy of the former is higher than that of the latter except when the prediction length is 1 day, and the maximum accuracy improvement is 25%. Both GRNN and GRNN＋AAM are stable, which illustrates that the prediction tendency of GRNN model as a whole is much more stable and GRNN model possesses perfect performance. The prediction time does not increase after introducing the AAM. The prediction

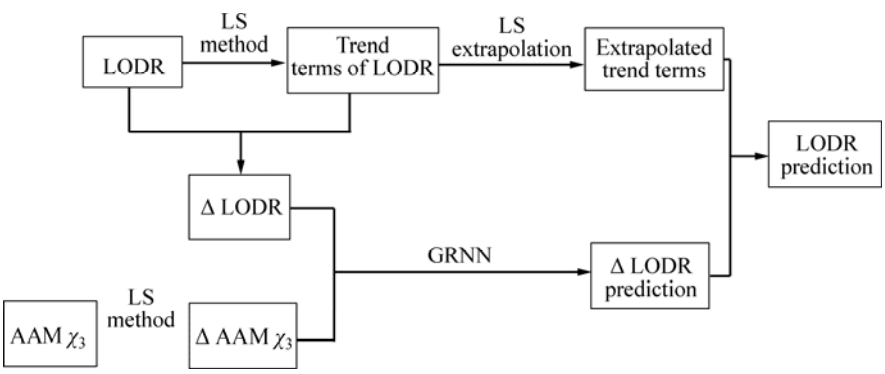

Fig. 3 Flow chart of introducing AAM to LODR prediction by GRNN

Table 1 Comparison of prediction results by three different models

Prediction length/d	BP	GRNN		GRNN+AAM	
	MAE/ms	MAE/ms	Improvement/%	MAE/ms	Improvement/%
1	0.028	0.045	—	0.048	—
2	0.074	0.068	8.1	0.074	0
3	0.095	0.088	7.4	0.096	1.1
4	0.111	0.104	6.3	0.110	0.9
5	0.131	0.119	9.2	0.122	6.9
6	0.151	0.135	10.6	0.140	7.3
7	0.162	0.137	15.4	0.134	17.3
8	0.169	0.148	12.4	0.139	17.8
9	0.176	0.153	13.1	0.148	15.9
10	0.189	0.164	13.2	0.154	18.5
12	0.193	0.187	3.1	0.184	4.7
14	0.211	0.186	11.9	0.158	25.1
16	0.213	0.193	9.4	0.168	21.1
18	0.215	0.197	8.4	0.179	16.7
20	0.217	0.195	10.1	0.171	21.2
22	0.216	0.230	-6.5	0.203	6.0
24	0.216	0.200	7.4	0.182	15.7
26	0.215	0.219	-1.9	0.173	19.5
28	0.218	0.215	1.4	0.183	16.1
30	0.219	0.205	6.4	0.172	21.5
60	0.273	0.247	9.5	0.229	16.1
90	0.303	0.261	13.9	0.228	24.8
120	0.312	0.297	4.8	0.256	18.0
150	0.334	0.312	6.6	0.267	20.1
180	0.358	0.331	7.5	0.305	14.8
210	0.387	0.351	9.3	0.291	24.8
240	0.391	0.374	4.4	0.321	17.9
270	0.399	0.404	-1.3	0.346	13.3
300	0.440	0.435	1.1	0.358	18.6
330	0.453	0.444	2.0	0.388	14.4
360	0.446	0.530	-18.8	0.427	4.3
Mean	—	—	6.1	—	14.7

accuracy of the GRNN model is 6.1% higher than that of BP network, which illustrates that the performance of GRNN is better than that of BP model in LOD prediction. After introducing the AAM, the prediction accuracy is further improved, by 14.7%. The results show that the atmosphere is the main excitation source of the LOD change, whose contributions are considered to result in significant improvement and the prediction accuracy of the LOD change.

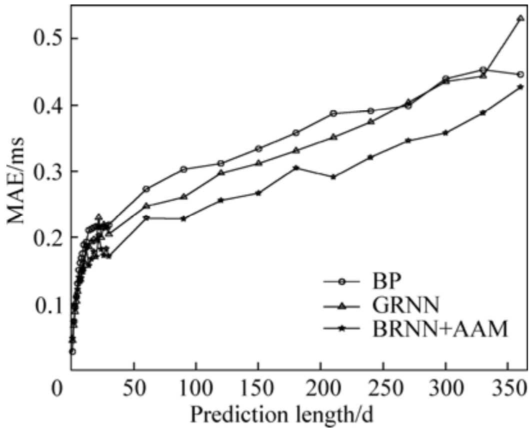

Fig. 4 Comparison of prediction results by different models

4 Conclusions

1) The non-linear GRNN method can not only acquire highly accurate prediction result, but also improve greatly the prediction efficiency, since only the smoothing factor is needed to adjust and the size of the sample required by the network training is much smaller than that of the BP neural network. Taking the prediction of the LOD change with the time span of 5 days as an example, the prediction of the LOD change made by the BP neural network needs to take over 10 h, while that by the GRNN method only needs 1 h, greatly increasing the prediction efficiency.

2) Considering that the axial AAM function is tightly correlated with the LOD change, we propose to combine the LODR and AAM to predict the LOD change due to the strong relationship between the LOD and AAM. The results show that after introducing the AAM, the prediction accuracy is further improved, by 14.7%. The atmosphere is the main excitation source of the LOD change, whose contributions are considered to result in significant improvement of the prediction accuracy of the LOD change.

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