RBF Prediction Model Based on EMD for Forecasting GPS Precipitable Water Vapor and Annual Precipitation

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Abstract. The forecast of precipitations is important in meteorology and atmospheric sciences. A new model is proposed based on empirical mode decomposition and the RBF neural network. Firstly, GPS PWV time series is broken down into series of different scales intrinsic mode function. Secondly, the phase-space reconstruction is done. Thirdly, each component is predicted by RBF. Finally, the final prediction value is reconstructed. Next, the model is tested on annual precipitation sequence from 2001 to 2010 in northeast China. The result shows that predictive value is close to the actual precipitation, which can better reflect the actual precipitation change. From 2001 to 2010, the maximum deviation of the predicted values never exceeds 4%. The testing results show that the proposed model can increase precipitation forecasting accuracies not only in GPS PWV but also in annual precipitation.

Introduction

Due to the diversity and the variability of the weather conditions, and precipitation process itself complex nonlinear, making it difficult to establish determine precipitation simulation and forecasting model, so most of the domestic and foreign precipitation forecasting methods are built on the historical data on the basis of statistical analysis[1~4]. For the GPS precipitable water vapor (GPS PWV) is important in precipitation forecast [5]. This paper proposed a new model such as RBF prediction model based on empirical mode decomposition (EMD) to forecasting GPS PWV. Next, the model is tested to forecast annual precipitation.

EMD method and eliminating the effect of EMD decomposition endpoint

EMD method is a signal analysis method which was put forward by Dr. Huang. It enables the processing of non-stationary data smoothly. Complex signal is decomposed into a finite number of intrinsic mode function (IMF). The IMF components contain the local characteristics of the different time scales of the original signal [6-8], Traditional forms of spectral analysis, assumed that either linear or nonlinear time series can be decomposed into a set of linear components. EMD method does not assume that a time series is linear or stationary prior to analysis. EMD adaptively decomposes a time series into a set of independent intrinsic mode functions (IMFs) and a residual component. IMFs, as a kind of functions defined by Norden in EMD algorithm, represent partial Hilbert transforms of the signal and possess properties such as smoothness in both frequency and amplitude modulation.

The decomposition is based on the following assumptions [6]:

(1) The signal has at least two extrema-one maximum and one minimum;

(2) The characteristic local time scale is defined by the time interval between two consecutive extrema;

(3) If the data is totally free of extrema but contain only inflection points, then the characteristic local time scales can be obtained by the integration of the components.

One-dimensional data of EMD is realized as follows:

Set $z(k)$ is obtained using the following procedure:

（1）Set $r_0(k)=z(k)$ and set $i=1$.

（2）Identify all of the extrema (maxima and minima) in $r_{i\text{-}1}(k)$.

（3）Compute a maximal envelope, $\max_{i\text{-}1}(k)$, by interpolating between the maxima found in step (2). Similarly compute the minimal envelope $\min_{i\text{-}1}(k)$. Cubic splines (as suggested by Norden appear to be the most appropriate interpolation method for deriving these envelopes in one dimension.

(4) Compute the mean value function of the maximal and minimal envelopes

$$m_{i-1}(k)=\frac{[\max_{i-1}(k)+\min_{i-1}(k)]}{2}$$

(5) The estimate of IMF is computed from $IMF_i(k)=r_{i\text{-}1}(k)-m_{i\text{-}1}(k)$.

Each IMF is supposed to oscillate about a zero mean and in practice it is necessary to perform a "sifting" process by iterating steps (2)~(5) (setting $r_{i\text{-}1}=IMF_i$ before each iteration) until this is achieved.

(6) Once IMF_i has a mean value that is sufficiently close to zero over the length of the data (defined by a stopping criterion within some predefined tolerance ε), the residual $r_i(k)=r_{i\text{-}1}(k)-IMF_i(k)$ is computed. Alternatively the sifting procedure can be stopped when the difference in the standard deviation of successive estimates of IMF_i falls below a critical threshold [6].

(7) If the residual $r_i(k)$ is a constant or trend then stop; else increment i and return to step (2).

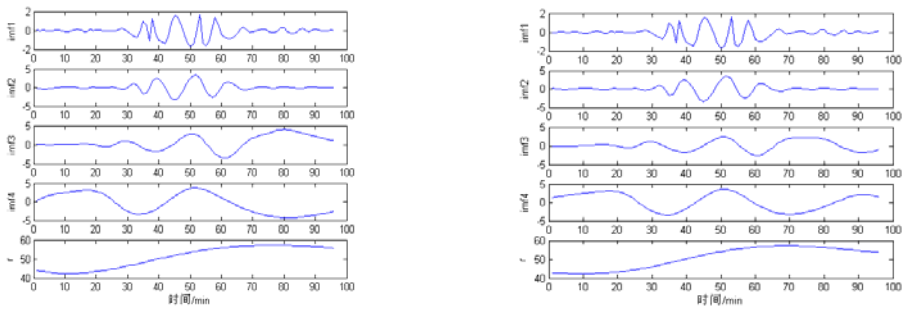
To reduce the screening step, SD parameter is defined and is expressed as:

$$\mathrm{SD}=\sum_{t=0}^{\mathrm{T}}\left[\frac{\left|h_{1(k-1)}(t)-h_{1k(t)}\right|^2}{h_{1(k-1)}^2(t)}\right],\quad k=1,2,\cdots \tag{1}$$

Stop when SD less than a constant.

In the case of the cubic spline, the decisions made there can potentially affect the envelope in the interior of the interval, propagating through the spline smoothness conditions imposed at the local extrema. Mirroring the function across the left and the right boundary, at least up to the first extremum present, has been reported to lead to good extrapolation result. RBF neural network is also a good method in disposal of boundary problem [9].

In this paper, the latter method was used to eliminate the effect of EMD decomposition endpoint. GPS data on July 27 15pm 2007 to July 28 15pm 2007 in Qinhuangdao station was selected. Contrast was shown as figure 1 (a) and (b).



（a）Decompose result with endpoint effect （b）Decompose result without endpoint effect

Fig.1 the result of GPS PWV decomposed by EMD

RBF prediction model of GPS PWV Based on EMD

RBF neural network can achieve very accurate approximation for hoping map, and it has strong generalization ability. Based on the signal sequence decomposition by the EMD, the data were preprocessed by using phase space reconstruction technology. Select GPS data from July 27, 2007 to July 28, 2007, from July16, 2007 to July17, 2007. Comparison was done between the forecasting GPSPWV based on EMD-RBF neural network, GPSPWV based on RBF neural network and the actual GPS PWV data. As shown in figures 2~5.

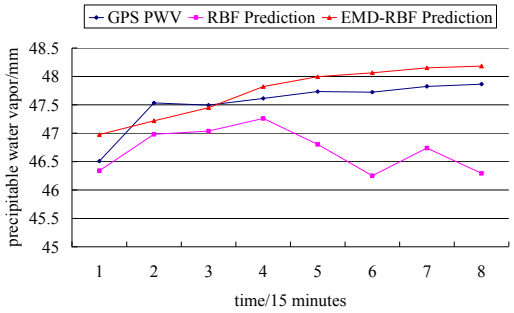


Fig.2 the comparison of 2h prediction of small fluctuation data

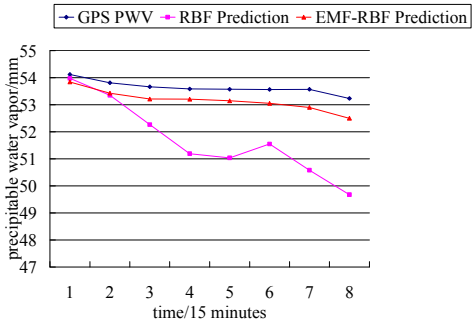


Fig.3 the comparison of 2h prediction of large fluctuation data

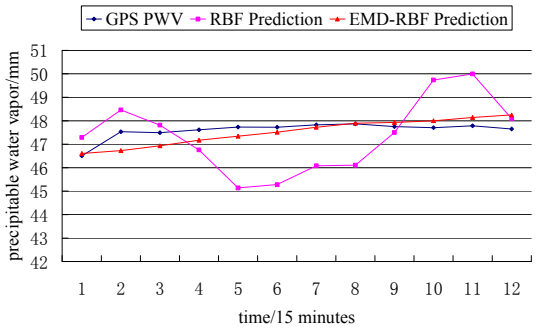


Fig.4 the comparison of 3h prediction of small fluctuation data

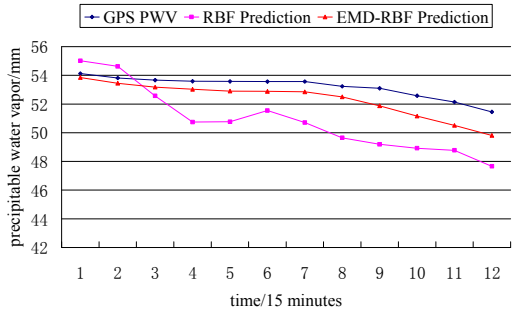


Fig.5 the comparison of 3h prediction of large fluctuation data

When the GPS PWV fluctuation is large:

The average deviation of GPS PWV prediction result based on EMD-RBF neural network and the GPS PWV is 0.86mm.

The average deviation of GPS PWV prediction result based on RBF and the GPS PWV is 2.64mm.

Comparing two hours predicted results as follows:

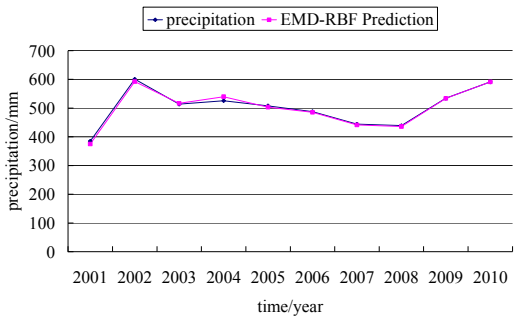
Average deviation of GPS PWV prediction result Based on EMD-RBF neural network and the GPS PWV is 0.48mm.

The average deviation of GPS PWV prediction result based on RBF and the GPS PWV is 1.94mm.

When the GPS PWV fluctuation is small, the according results are: 0.34mm, 0.29mm, 1.36mm and 0.82mm.

RBF Prediction model of Annual precipitation Based on EMD

As shown in figure 6~ figure 7, EMD-RBF neural network predictive value is close to the actual precipitation, which better reflects the actual precipitation change. From 2001 to 2010, the maximum deviation of the predicted values never exceeds 4%.



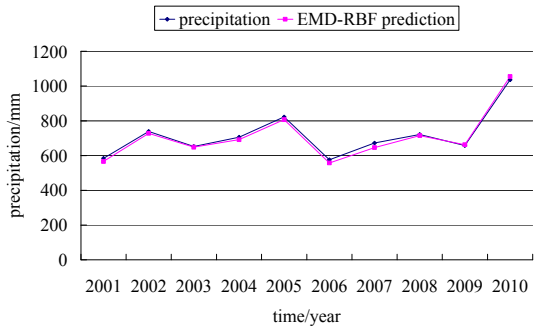


Fig.6 the comparison between the precipitation prediction of EMD-RBF neural network and the actual precipitation in Haerbin

Fig.7 the comparison between the precipitation prediction of EMD-RBF neural network and the actual precipitation in Shenyang

More contrast test was done and shown in table 1.

Table 1 comparison between the precipitation prediction of EMD-RBF neural network and the actual precipitation

station	average absolute relative error（%）	average absolute relative error（%）	correlation	the maximum relative error（%)
Anda	3.97	2.49	0.977	12.09
Fujin	2.57	1.8	0.991	7.93
Haerbin	0.99	0.34	0.996	-2.67
Hailun	4.41	-0.97	0.989	-14.77
Huma	2.95	-2.21	0.990	-7.31
Jixi	3.08	1.61	0.981	8.84
Keshan	4.87	4.87	0.996	8.56
Mudanjiang	6.94	5.40	0.961	10.57
Nenjiang	4.99	-1.61	0.951	7.64
Qiqihaer	4.01	0.04	0.988	-14.67
Shangzhi	2.04	-0.94	0.985	-5.58
Suifenhe	2.33	0.97	0.989	4.13
Sunwu	4.62	-0.63	0.989	-9.59
Tonghe	4.74	0.10	0.960	8.80
Changchun	3.52	2.20	0.937	10.92
Linjiang	3.87	2.11	0.986	10.08
Qianguoerluosi	4.39	1.38	0.977	7.45
Siping	2.32	0.15	0.998	-6.90
Yanji	3.54	1.98	0.993	6.09
Benxi	5.37	3.92	0.949	10.09
Chaoyang	3.91	-1.30	0.989	-7.22
Dalian	5.57	3.44	0.976	12.49
Dandong	2.57	1.39	0.977	8.75
Jinzhou	4.65	1.41	0.971	10.99
Shenyang	1.95	1.47	0.998	3.97
Yinkou	3.98	2.93	0.988	8.54
Zhangwu	5.80	1.87	0.937	-14.63

Totally speaking, the correlation between predictive value based on EMD-RBF neural network and precipitation are more than 0.9. The mean absolute relative error and average relative errors are less than 7%. The maximum relative error of is within 10%. The maximum relative error never exceeds 15%.

Summary

This study focused on the test of prediction on EMD- RBF neural network. The results showed that the prediction of decomposed signals is superior to direct prediction. The test results show that

EMD-RBF neural network has important practical significance for not only accurately GPS PWV prediction, but also precipitation prediction.

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