A weighting function approach for neural network nonlinear time series analysis of satellite remote sensing of rainstorms

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Abstract*— One of frequently used neural networks, i.e., a radial-based function network (RBFN) with Gaussian activation functions is employed to study the nonlinear time series by carrying out the characterization experiments for a GMS-5 satellite 11μm IR observations of rainstorm process. The proposed methodology mainly uses RBFN to approximate the nonlinear time series signal first; then the characteristics of its weighting functions changed with time are analyzed. The difficulty due to the effects of high noise on the signal processing using neural networks is addressed. Thus, finally a more integrated method combining the neural network analysis with wavelet packet decomposition is introduced. The preliminary results show that the proposed approach for nonlinear time series analysis is efficient and promising.

I. INTRODUCTION

In recent years, extreme weather events, such as severe storms and extreme rainfalls, have been increased likely worldwide, especially over Europe and Asian monsoon regions [1], which have caused, and will still frequently cause great or sudden disasters, with terrible accidents of human lives and economic society in the world. The knowledge of formation and evolution of rainstorms, and their forecasting are crucial to studies of weather, climate, and environment problems. It is difficult to solve the satellite retrieval problems in cloudy atmospheres with rainstorms using the traditional and classical optical retrieval approach. Therefore, it is imperative to develop new and modern retrieval theories and methods for satellite optical remote sensing of storms.

We can imagine that the evolution of storm process is a nonlinear dynamic process, with chaos and fractal properties [2]. Thus, to develop a new and modern satellite remote sensing method to reveal the occurrence and evolution process of severe storms, we would like to combine satellite remote sensing with nonlinear sciences to study the issues.

Chaotic systems are an important class of dynamical systems. Often, the only information we have about such systems is in the form of a time series. The process of analyzing time series constitutes a field of science known as time-series analysis. Its objective is to build a model for the unknown dynamical system that generated the time series.

Chaotic time-series analysis, or nonlinear time-series analysis, cannot be studied satisfactorily by linear time series analysis, which fails to detect any nonlinear correlations present and cannot provide a complete characterization of the underlying dynamics and, thus, describe the nonlinear structure in chaotic time series. However, uncovering the deterministic structure is important because it allows for construction of more realistic and better models and thus improved predictive capabilities.

Over the last two decades many nonlinear time series methods have been developed in the theory of nonlinear dynamics, commonly known as chaos theory. Since artificial neural networks are a high complex nonlinear dynamical system with powerful signal processing capability and have all demonstrated superior performance in many engineering applications, in this paper we would like to use neural networks combined with wavelet analysis to study the nonlinear time series of satellite remote sensing of rainstorm process. The preliminary results show that the proposed approach of neural network weight series combined with wavelet packet decomposition has potential for nonlinear time series analysis with high noise effects.

II. Neural network nonlinear time series prediction

Neural networks have been applied to many areas of statistics, classification and pattern recognition, and time series analysis. In many areas of statistics, especially in time series analysis, neural networks play an important role. The historical development of neural computation is written in some books [3,4].

There are two kinds of time series, i.e., linear time series and nonlinear time series, or chaotic time series. For time series analysis, the very first object of the study is forecasting, which is one of controversial domain and the subject of a tremendous effort in research and development. Time series forecasting can be studied using well-established statistical models, which, however, have some drawbacks as pointed out by Hill et al. [5] and Kajitani et al. [6], thus, are not suitable for nonlinear time series forecasting. Some approaches for nonlinear time series forecasting are commonly used, for example, chaos model, neural network model, and random work model, etc.. Especially, since the last decade in 20 century, a considerable attention has been devoted to dynamical system theory for the study of nonlinear time series. It is worth pointing out that the starting point of dynamical system time series analysis is the determination of past series information to be

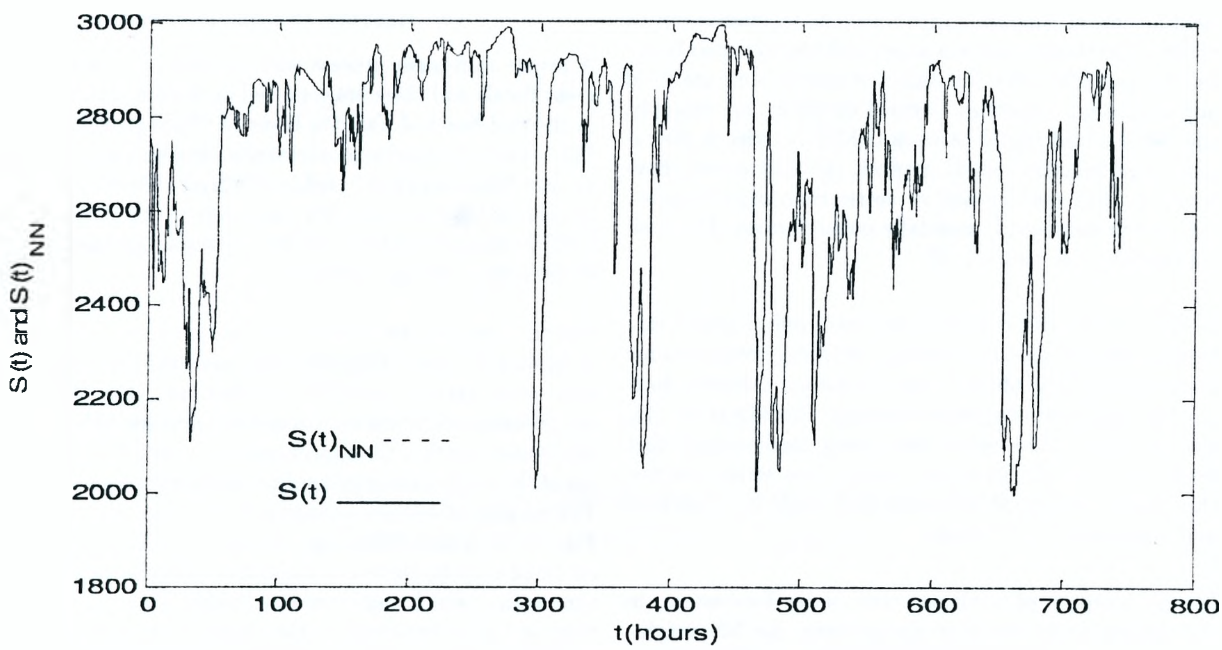

Fig. 1, GMS-5 observation time series S (t) in Wuhan in July 1998 (solid line), and its approximation time series $S(t)_{NN}$ by RBFN (dashed line). The time t ranges from 1 July to 31 July with 744 hours.

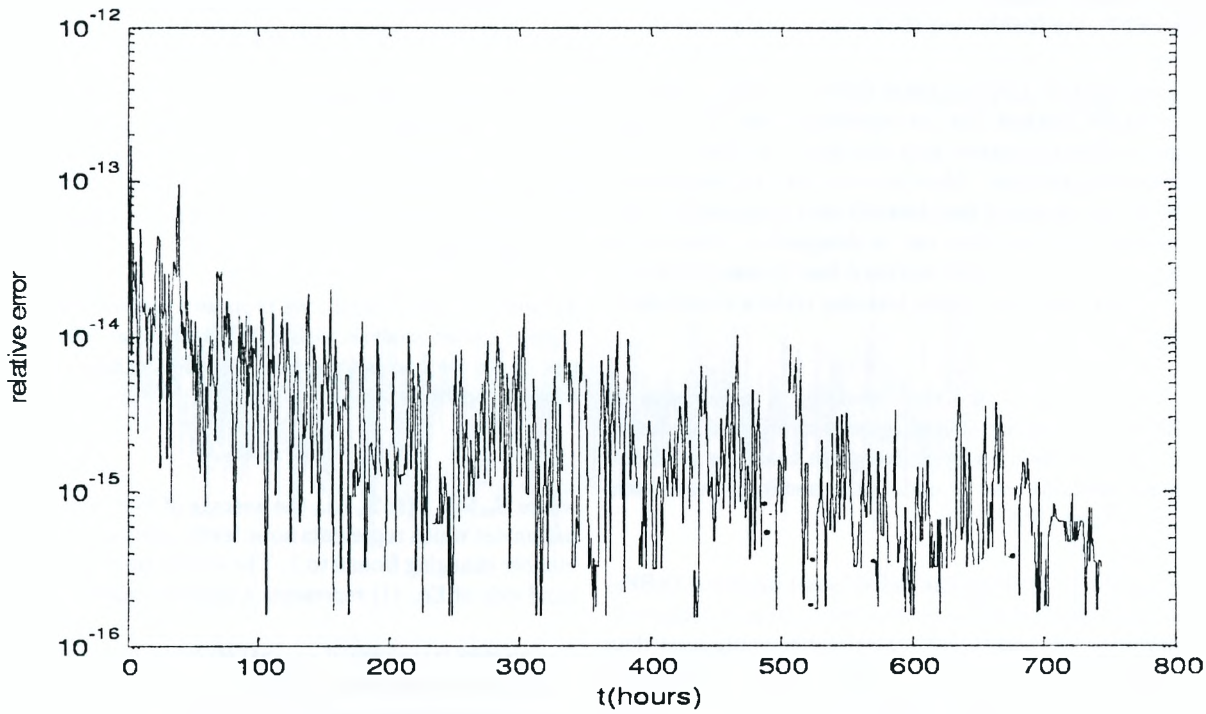

Fig. 2 The relative error of the approximation of RBFN to the signal of the GMS-5 observation time series S(t) changes with time t.

used for model building. Once this is done, models can be constructed through several ways, and neural networks are natural candidates for this task because of their universal approximation properties. Neural networks, for example, the feed forward neural network (FFNN) model or the radial based function neural network (RBFN) model, have been found to work as well or better than many competing models mentioned, especially outperformed the classical random walk model [6-9].

Golovko et al. [10] discuss a synthetic use of neural networks to chaotic signal processing, including nonlinear time series analysis, the identification of chaotic behavior, forecasting and dynamical reconstruction. Pavlidis et al. [11] also propose a time series forecasting methodology that draws from the disciplines of chaotic time series analysis, clustering, and neural networks, and apply it to perform multi-step-ahead prediction.

For the purpose of nonlinear time series forecasting, in the present study, we shall alternatively use NN weighting function Cbased approach to characterize the nonlinear time series, first.

III. Radial basis function neural network

In the literature a large variety of neural networks has been proposed for modeling the dynamic behavior of a system. Three types of neural networks are frequently used, i.e., the FFNN, the RBFN, and the Elman neural network [12].

Jayawardena et al.[9] found that RBFN is similar to FFNN. The RBFN method has the advantage that it does not require a long calculation time and does not suffer with the overtraining problem. More neurons may be required for RBFN than standard feed-forward back propagation (BP) networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. Thev work best when many training vectors are available [13].

It is commonly known that linearity in parameters in RBFN allows the use of least squares error based updating schemes that have faster convergence than the gradient-descent methods used to update the nonlinear parameters of multi-layer BPNN.

Furthermore, Gaussian-like radial based functions (RBFs) are local (give a significant response only in a neighbourhood near the centre) and are more commonly used than multiquadric-type RBFs which have a global response. Its expression is simple and the analyticity is good. Thus, in this paper, RBFN with Gaussian activation functions is employed.

IV. Results and discussions

A severe rainstorm process with sudden occurrence and great floods and disasters occurred in Wuhan area located in the mid basin of Yangtze River in China on 21-27 July 1998. The corresponding observation time series of Geostationary Meteorological Satellite (GMS)-5 11μm IR channel brightness temperatures (BT) are used in this study since GMS-5 observations have higher time resolution than those of the polar-orbiting satellites.

Figure 1 depicts the GMS-5 observation time series $S(t)$ in Wuhan in July 1998(solid line), and its approximation time series $S(t)_{NN}$ by RBFN (dashed line). Fig. 2 shows the relative error of the approximation changes with time t, demonstrating that the approximation of RBFN to the signal of the GMS-5 observation time series $S(t)$ is very good. The weights of $S(t)_{NN}$ changing with time are plotted in Fig. 3. It is seen from Fig. 3 that at $t{\approx}300$ hours, i.e., on 12-13 of July, there is a dramatic change in the weight time series, which indicates that before about one week there is a remarkable sign in the weight time series $S(t)_{NN}$ prophetic of the occurrence of severe rainstorm process.

In our further study of the same rainstorm process using the new quantities defined by inter-discipline of fractal and wavelet packet, similar results are obtained, which will be published elsewhere.

The effects of noise on the weight time series $S(t)_{NN}$are shown in Fig.4, assuming that the time series $S(t)$ is contaminated by the noise with the ratio of noise to signal being 0.01, 0.05 and 0.1, respectively.

It is obvious by comparison of Fig.3 and Fig.4 that with the increase of noise, the characteristic with the remarkable sign in the weight time series $S(t)_{NN}$ mentioned above is disappeared gradually. So, signal processing using neural network time series analysis with high noise is also a challenging problem.

To overcome the difficult, we propose a method combined wavelet packet analysis with RBFN technique. The objective of the method is to remove the effect of noise. Define a new quantity as:

$$S^*(t) = S(t) + \delta S_m \eta \tag{1}$$

where $S_m =< S(t) >$, i.e., the average of $S(t)$, δ denotes a parameter which represents noise level, η denotes a random number changing from 0 to 1. The second term in the right hand side of Eq. (1) represents a random noise.

The wavelet transform of a signal evolving in time provides a tool for time-frequency localization [14]. It is known that the wavelet packets method is a generalization of wavelet decomposition, which can be used for numerous expansions of a given signal, and thus, offers a richer signal analysis. Thus, for analyzing the time series $S^*(t)$, the discrete

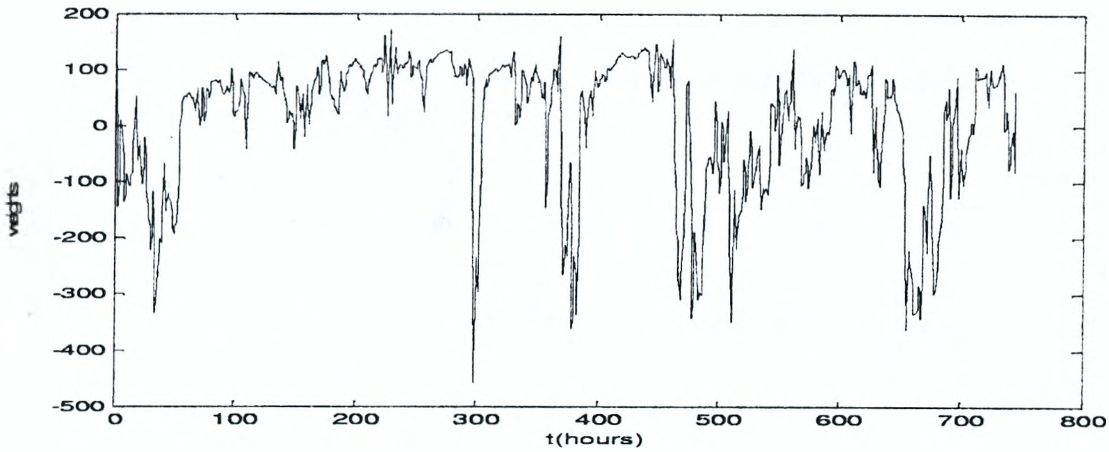

Fig. 3, The weights of the signal $S(t)_{NN}$ approximated by RBFN to the time series S(t) change with time t. Suppose $\delta = 0$.

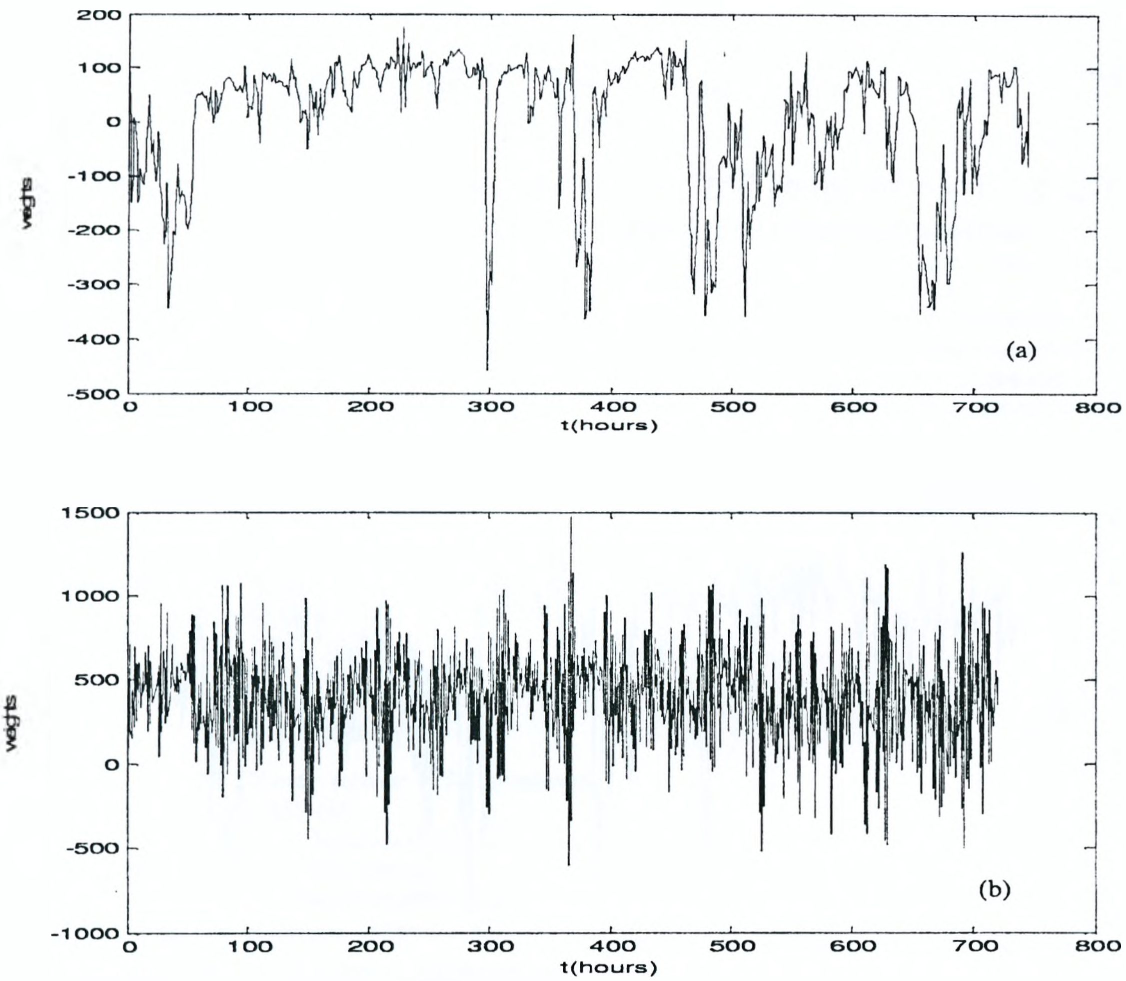

Fig. 4, The effects of noise on the weight time series of $S(t)_{NN}$ with with (a) $\delta = 0.01$ and (b) $\delta = 0.1$, respectively. For saving the space, the figure for δ being 0.05 is omitted.

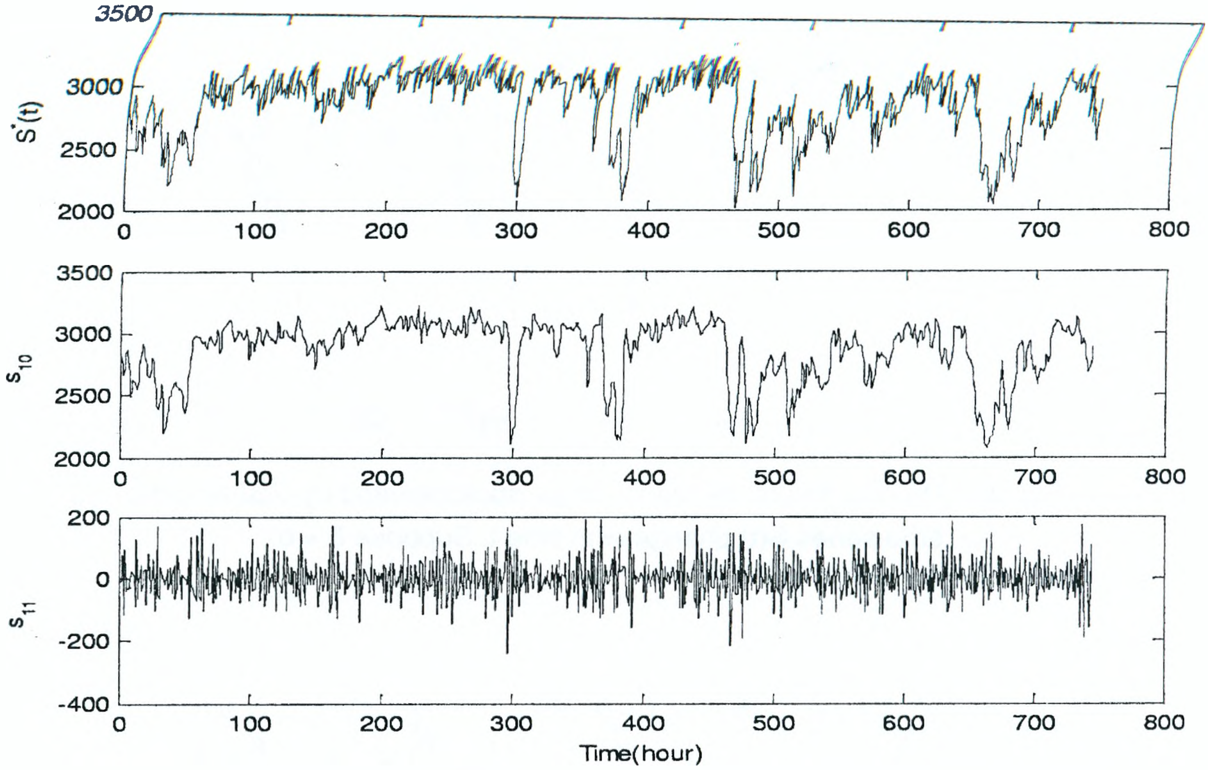

Fig. 5, The time series S*(t) and the two elements, s_{10} and s_{11}, in the DWPT decomposition with level $j = 1$ for S*(t).

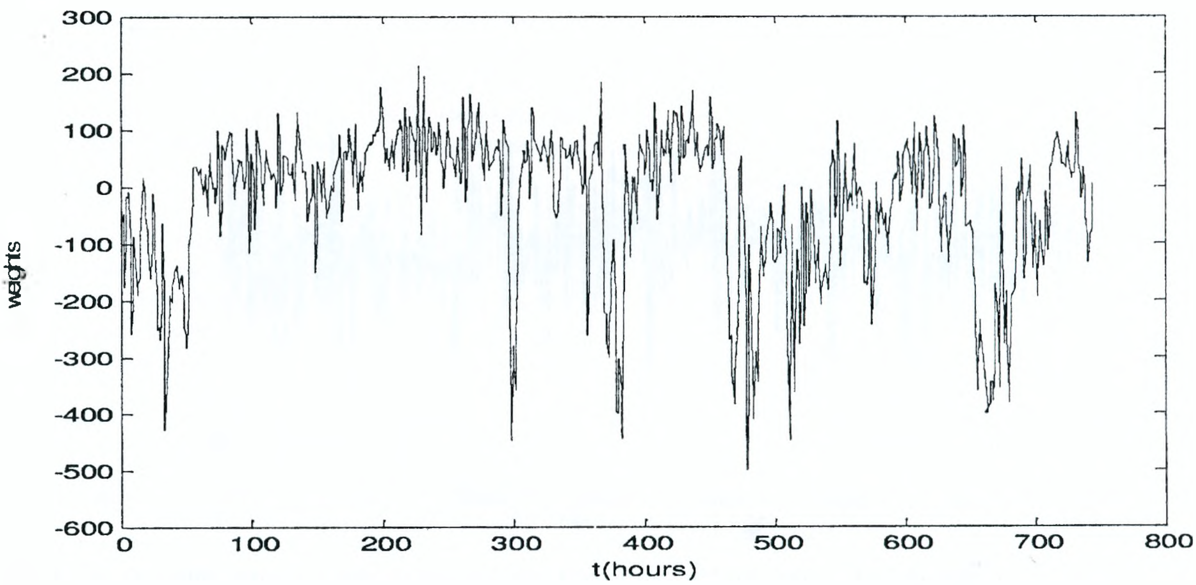

Fig. 6, The effects of noise on the weight time series of s_{10NN} with the parameter $\delta = 0.1$.

wavelet packet transform (DWPT) [14,15] is used. Fig.5 shows the DWPT decomposition with level $j = 1$ for the time series $S^*(t)$ and the 2 elements in the first level in the decomposition. It is obvious that the element s_{10} is mainly composed of low frequencies, and the element s_{11} is composed of high frequency including the noise.

Motivated by the results of the wavelet packet decomposition, we perform the RBFN time series analysis for the element s_{10}. The weights of the signal s_{10NN} approximated by RBFN to the time series s_{10} changing with time t are plotted in Fig.6, which depicts the effects of the noise with $\delta= 0.1$ on the weight time series. Obviously, the dramatic change of the weight series at $t\approx 300$ hours still appears in Fig.6. This indicates that the approach of combination of wavelet packet with RBFN is effective for the signal processing with higher noise.

V. CONCLUSION

Forecasting of extreme weather and climate events using satellite remote sensing time series is important and of signal processing problems which is challenging due to small sample sizes, non-linearity, and complexity of the system. Neural networks have been very successful in a number of signal processing applications.

This paper presents an approach for a nonlinear time series analysis and applies it to characterize the GMS-5 satellite 11μm IR channel BT observation time series of rainstorm process and the noise effects are addressed. The proposed approach draws from the disciplines of the neural network and wavelet analyses. First, the RBFN is used to approximate the nonlinear time series. Then, the weight series is analyzed for characterizing the time series for its further forecasting study. Finally, since the effects of noise on the signal processing often occur, the DWPT decomposition is employed for overcoming the difficulty. The preliminary results demonstrate that this approach for characterization of nonlinear time series with higher noise is efficient and promising and, thus, needs further effort in research and development.

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