Data Fusion of Multivariate Time Series Based on Local Maximum Weighted Coefficient

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Abstract: In this paper, a novel fusion data algorithm is proposed via local Maximum weighted coefficient algorithm. For effectively fusing multivariate time series and reserving the motion information of original system, the weighted coefficients are rationally estimated the fusion state. Experimental results show that the algorithm can obtain desirable results on Lorenz model and multi-lead ECG signals.
Keywords: Data fusion, Maximum weighted coefficient

1. Introduction

As the important analytical tool for nonlinear system, phase space reconstructed theory is widely applied [1-9]. Based on phase space reconstruction theory, the motion information of complex nonlinear systems could be reflected in high-dimensional space effectively. A great of researches show that via multivariable phase space reconstruction theory, the feature of chaos can be described better.

Chaos time series prediction is a fundamental issue of chaos theory and many prediction algorithms have been proposed [10, 11]. Local prediction algorithm of chaos time series has better performance. In this algorithm, some neighbor states on evolutionary trajectory are used to predict their future states by a linear prediction model. Inspired by local weighted linear prediction algorithm, the idea of the algorithm is employed appropriately in data fusion of multivariate time series.

The outline of the rest of this paper is as follows. Section 2 introduces our method which is based on the local weighted linear prediction algorithm. Our algorithm is applied to Lorenz model and multi-lead ECG signals in Section 3. Section 4 is the conclusion.

2. Multivariate Data Fusion via Local Maximum Weighted Coefficient

For a chaotic time series, suppose that X_k is the current state point of the chaotic system and its next step X_{k+1}, the future state of the system need to be predicted. In the local weighted linear prediction algorithm, the neighbor state points of the current state point X_k need to be selected in reconstructed space. Utilizing the state information of neighborhood X_{ki} and linear prediction model, the future state X_{k+1} can be approximately estimated.

The steps of our method are listed as follows.

(1) Select proper parameters of embedding dimension m and delay time τ, and the vectors is constructed as

$$X_t = (x(t), \cdots, x(t+(m-1)\tau)) \in R^m, \tag{1}$$

where $t = 1, 2, \cdots, N-(m-1)\tau$.

(2) Calculate the Euclidean distances between the X_k and other neighbor state vectors $\{X_{ki}, i = 1, 2, \cdots, n\}$

$$d_{ki} = \|X_{ki} - X_k\|_2 , \tag{2}$$

and, utilizing the distance information, the weighted coefficient of each neighbor state vectors X_{ki} can be computed as

$$\omega_{ki} = \frac{\exp[-\lambda(d_{ki} - d_{\min})]}{\sum_{i=1}^{n} \exp[-\lambda(d_{ki} - d_{\min})]} , \tag{3}$$

where d_{min} is the minimum distance in $\{d_{ki}, i = 1, 2, \cdots, n\}$ and λ regularization parameter is usually set to 1.

(3) Estimate the future state X_{k+1} via maximum weighted coefficient

$$X_{k+1} = X_{kj} , \tag{4}$$

where X_{kj} is chosen from all neighbor state vectors $\{X_{ki}, i = 1, 2, \cdots, n\}$, that the weighted coefficient ω_{kj} of X_{kj} is the maximum value in $\{\omega_{ki}, i = 1, 2, \cdots, n\}$.

(4) The predicted value of chaotic time series can be extracted from the state vectors X_{k+1}.

3. Experiment

3.1. Application of Lorenz model

Here, Lorenz model is employed to illustrate the performance of our method and the model can be formulated as

$$\dot{x} = \sigma(y - x) , \tag{5}$$

$$\dot{y} = x(r - z) - y , \tag{6}$$

$$\dot{z} = xy - bz , \tag{7}$$

where the parameters σ, r and b are usually set to 10, 28 and 8/3, respectively [12]. In the experiment, the embedding dimension m and the delay time τ are chosen to be $m = 4$ and $\tau = 16$ [10] and initial values of the system are $x = 0.1, y = 0.1, z = 0.1$.

The final fused result is shown in Figure 1. In the figure, we can find that the reconstructed trajectory of fused result shows the shape of the "8" and the shell shape. Apparently, the fused result could reflect the characteristic of Lorenz model objectively and the method can effectively reserve the characteristic information of the model in final result.

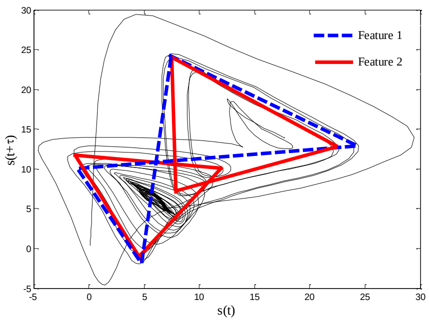

Figure 1. Fused result of the novel fusion data algorithm.

3.2. Application of 12-lead ECG Signals

The activity of heart is presented as physiological electrical signal on the surface of human body. An electrocardiogram (ECG) records the cardiac activity by using some electrodes which closely touch the skin of body, containing a generous amount of information on the condition of cardiac work. Therefore, ECG recordings have been widely applied to clinic diagnosis and clinical monitor. Once facing 12-lead ECG signals, each lead of ECG signals must be processed individually by assessment algorithm and apparently the computing efficiency of these methods is less effective. The key solution lies in converting the 12-lead ECG signals into a single physiological signal while the quality characteristics of original signals are reserved as much as possible. In subsection 3.2, our method will be applied for 12-lead ECG signals.

In this part, the ECG signal is chosen from the database of PhysioNet/Computing in Cardiology Challenge 2011. The data are standard 12-lead ECG signal which is sampled at 500Hz and all leads are recorded simultaneously for 10 seconds. The two sets of realistic 12-lead ECG signals are selected. Thereinto, the signals No.1027085 is acceptable and the No.1063069 is unacceptable.

Via our method, the reconstructed trajectory of fused result for the signal No.1027085 is shown in Figure 2. As the qualities of ECG signal is acceptable, it is easy to find that the fused signal presents the periodic changes and possess significant physiological meaning. Further, the reconstructed trajectories of fused result obviously show the regular evolutionary trajectory. On the other hand, the other is unacceptable. From the Figure 3, the fused result reflects disorderly and unsystematic evolutionary characteristic. So we couldn't achieve any significant physiological information.

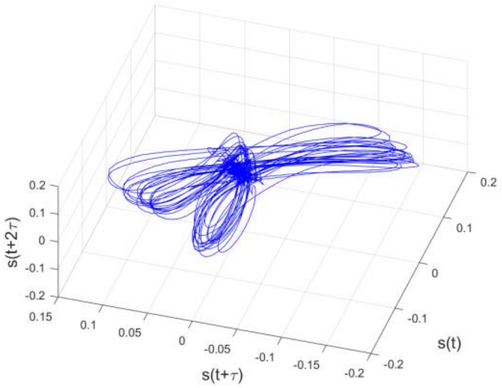

Figure 2. The fused result of the signal No.1027085.

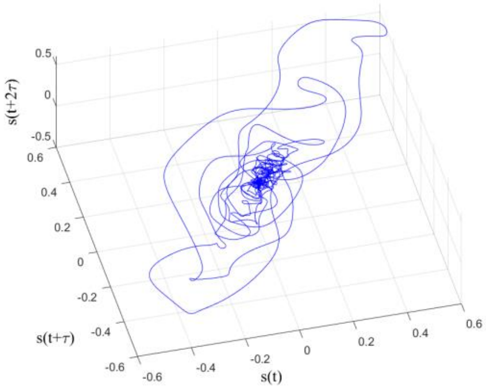

Figure 3. The fused result of the signal No. 1063069.

4. Conclusion

In this study, Lorenz model and realistic ECG signals are used to test the validity of our algorithm. The experimental results presented show that the data fusion of multivariate time series based on local maximum weighted coefficient algorithm could effectively fuse multivariate time series and well reserve the characteristic information of original signal.

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References

[1] G.D.Clifford, "ECG Statistics, Noise, Artifacts, and Missing Data", *Engineering in Medicine and Biology*, 1st ed., Norwood, MA, USA: Artech House, Oct. 2006.

[2] J. Behar, J. Oster, *et al.*, "ECG Signal Quality During Arrhythmia and Its Application to False Alarm Reduction", *IEEE Trans. Biomed. Eng.*, vol. 60, pp.1660-1666, 2013.

[3] G. B. Moody, R. G. Mark, "QRS morphology representation and noise estimation using the Karhumen-Loeve transform", *Comput. Cardiol.*, vol. 16, pp. 267-272, 1989.

[4] J. Allen, A. Murray, "Assessing ECG signal quality on a coronary care unit", *Physiol. Meas.*, vol. 17, pp. 249-58, 1996.

[5] I. Silva, *et al.*, "Improving the quality of ECGs collected using mobile phones: the PhysioNet/Computing in Cardiology Challenge 2011", *Comput. Cardiol.*, vol. 38, pp. 273-276, 2011.

[6] N. Kalkstein, *et al.*, "Using Machine Learning to Detect Problems in ECG Data Collection, the PhysioNet/Computing in Cardiology Challenge 2011", *Comput. Cardiol.*, vol. 38, pp. 437-440, 2011.

[7] V. Chudacek, *et al.*, "Simple Scoring System for ECG Quality Assessment on Android Platform, the PhysioNet/Computing in Cardiology Challenge 2011", *Comput. Cardiol.*, vol. 38, pp. 49-451, 2011.

[8] S. Zaunseder *et al.*, "CinC Challenge – Assessing the Usability of ECG by Ensemble Decision Trees, the PhysioNet/Computing in Cardiology Challenge 2011", *Comput. Cardiol.*, vol. 38, pp. 277-280, 2011.

[9] I. Jekova, *et al.*, "Recognition of Diagnostically Useful ECG Recordings: Alert for Corrupted or Interchanged Leads, the PhysioNet/Computing in Cardiology Challenge 2011", *Comput. Cardiol.*, vol. 38, pp. 429-432, 2011.

[10] J. L. Qu, *et al.*, "An Improved Local Weighted Linear Prediction Model for Chaotic Time Series", *CHIN. PHYS. LETT.*, vol. 31, 020503, 2014.

[11] B. Samanta, "Prediction of chaotic time series using computational intelligence", *Expert Systems with Applications*, vol. 38, pp. 11406-11411, 2011.

[12] Q. F. Meng, *et al.*, "The improved local linear prediction of chaotic time series", *Chinese Physics*, vol. 16, pp. 3220, 2007.