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Prediction of ECG Signal Based on TS Fuzzy Model of Phase Space Reconstruction

Fang Su, Hongsheng Dong
Lanzhou Institute of Technology
Lanzhou, China

Abstract—**ECG is an important gist for the diagnosis of heart disease, it is significant for heart disease warning in advance and ECG data repairing to predict ECG signal accurately. In this paper, the chaotic characteristics of ECG signal have been analyzed, and the ECG signal prediction based on the combination of the phase space reconstruct of ECG signal and the TS fuzzy model is proposed. The simulation experiment dealing with the typical nonlinear MG time series and the ECG data of MIT-BIH standard database shows that, and compared with other prediction algorithms, the proposed method achieves a better prediction performance, and which provides a new method for the processing of ECG data and the diagnosis of heart diseases.**

Keywords-ECG signal; Chaotic characteristics; Phase space reconstruction; TS fuzzy model; Signal prediction

I. INTRODUCTION

Heart disease is one of the most frequently occurring diseases, it has the characteristic of the illness hidden, easy recurrence, more complications, high mortality, and is seriously threatening the human life and health. According to the World Health Organization, there are approximately 17 million people worldwide each year, who die from various cardiovascular diseases[1]. Electrocardiogram (ECG) is an objective representation of cardiac electrical activity, and reflects the cardiac status at different levels and is the most common method of examining cardiac function clinically. Therefore, accurately and timely prediction of high-risk cardiovascular diseases by ECG signal is an important issue in clinical medicine and biomedical engineering fields.

The clinical electrocardiogram monitoring needs to save a large amount of ECG data. If the upcoming ECG signal is predicted by ECG historical data accurately, it is meaningful to reduce the storage of ECG data and to repair lost and damaged ECG data, more important is that it may provide some valuable diagnostic information for the early warning of heart disease. ECG signal is a nonlinear, non-stationary physiological signal with chaotic characteristics, it is more difficult to establish prediction model of ECG signal. Reference [2-3] presents a three-dimensional dynamic model of ECG constructed three ordinary differential equations, there is a very close similar between simulation ECG waveforms of model and the actual ECG signal, and it provides an effective tool for testing different analysis algorithms of ECG signal.

Nonlinear models are widely used in time series prediction[4-7], such as multi-layer perceptron neural networks (MLP), genetic algorithm (GA), support vector machines (SVM), and fuzzy neural network (FNN), etc. The prediction algorithm of ECG signal based on various neural network is proposed[8-9]. Although the neural network is of the strong self-learning and prediction ability, and also is very effective for dealing with nonlinear signals, but there still exists some imperfection in the process, for example, the RBF neural network is prone to generate too large or too small network structure, the MLP neural network is easy to cause over-fitting and trap into diffusion of gradients, and there is also the local optimum and over-learning disadvantage of BP neural network algorithm, which will affect the precision of prediction and generalization performance[10-11].

TS fuzzy model depicts the nonlinear system by linear subsystem combination, it demonstrates that TS fuzzy model has good localization feature and can approximate nonlinear systems with arbitrary precision, and has extremely good effect for the model identification and prediction of nonlinear system[12-14].The phase space reconstruction of nonlinear dynamics is a new method of time series analysis, the method needn't establish subjective models in advance, while models prediction based on the objective laws of sequence itself, which can effectively avoid the subjectivity of prediction, and improve prediction accuracy and credibility[15-16]. In this paper, the nonlinear chaos property of ECG signal is proved, and a new method of modeling and prediction for ECG signal is proposed, which combines with phase space reconstruction and TS fuzzy model, and this method provides a new idea for the processing of ECG data and the diagnosis of heart diseases.

II. METHOD

A. *Chaotic characteristic recognition of ECG signal*

The feature of chaotic systems can usually be described by the saturation correlation dimension, the maximum Lyapunov exponent and the Kolmogorov entropy, which reflect the inherent randomness, the initial value sensitivity of the system, and the irregular order within the system. In fact, the K entropy is zero for the regular ordered time series, while the K entropy is greater than zero for the chaotic sequence; and the maximum Lyapunov exponent is greater than zero for the chaotic time series. The cardiac system is a nonlinear complex system, so the ECG signal is of also nonlinear, non-stationary features, which many studies have shown that ECG signal contains certain chaotic components[17-19]. In this paper, the change of K entropy of ECG signal with the embedding dimension is analyzed by the GP algorithm, and only to test the chaos characteristic of ECG signal[20].

B. *Phase space reconstruction of ECG signal*

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Takens theorem states that the evolution of any system component also implies the information of evolution for the correlation components in the system[21].Therefore, after selecting the appropriate delay time τ and embedding dimension m for the time series, a phase space can be reconstructed by the system component, which is equivalent to the prime dynamics system, and the reconstructed phase space contains all the information of the original time series.

Set the ECG time series $\{x_1, x_2, ..., x_N\}$, then the m-dimensional ECG reconstructed vector $X(t) = \{x_t, x_{t+\tau}, ..., x_{t+(m-1\tau)}\}$,where m is the embedding dimension and τ is the delay time, $t = 1,2,..., N-(m-1)\tau$.

The prediction model of ECG signal of reconstruction space can be expressed as $y(t+\Delta t) = f(X(t))$,where y is the prediction model output, $X(t)$ is the model input vector, and the single step prediction is used, namely $\Delta t = 1$. Since the reconstruction phase space of ECG sequence and the original sequence contain the same topology information. Therefore, it is effective for the output of ECG prediction model based on the reconstruct of phase space.

The phase space reconstruction needs to determine two key parameters, that is, embedding dimension m and delay time τ . Here, the values of m and τ are calculated by the false neighbor method and the average displacement method, respectively.

Assumption, when the embedding dimension is m, the nearest neighbor of the input vector $X(t)$ is $X(t')$,the distance between the two is expressed as:

$$D^m(t) = \|X(t') - X(t)\| . \tag{1}$$

where $D^m(t)$ represents the distance in the m dimension.

This distance will change as the dimension increases from m to m+1, and let the new distance be $D^{m+1}(t)$ .If the formula (2) is satisfied, then $X(t')$ is called the false neighbor of $X(t)$.

$$\frac{D^{m+1}(t) - D^m(t)}{D^m(t)} > R_T . \tag{2}$$

where R_T represents a threshold, which general value ranges from 10 to 50.

For a chaotic ECG sequence, the proportion of its nearest neighbor is calculated, and gradually increase the dimension m until the proportion of the false nearest neighbor is less than 5% or the false nearest neighbor no longer decreases with increasing m, it can be considered that the chaotic dynamics has been fully developed, and the m at this point is the suitable embedding dimension [22].

After determining the embedding dimension m of the phase space reconstruction of ECG signal, the determine of the delay time τ is calculated by the average displacement method. The average displacement (AD) of two adjacent points in the phase space is defined as:

$$AD(m,\tau) = \frac{1}{k}\sum_{n=1}^{k}\sqrt{\sum_{l=1}^{m-1}(x_{n+l\tau} - x_n)^2} . \tag{3}$$

where m is the embedded dimension and k is the total number of multi-dimensional vectors of the reconstructed system, $k = n-(m-1)\tau$.

Make the curve of the $AD(m,\tau)$ and the slope of the $AD(m,\tau)$ following the change of delay time τ , and τ is taken the integral multiple of the sampling time, when the slope of the $AD(m,\tau)$ curve reduces to 40% of its initial slope, the τ at this time is the optimal delay time [23].

C. TS fuzzy prediction model for ECG signal

1) TS fuzzy model structure

The TS fuzzy model describes a nonlinear system by means of a set of "if-then" fuzzy rules. Let there are c rules for the TS model, and the i-th fuzzy rule R^i in the former c-1 rules is:

R^i :if x_1 is A_1^i ,and x_2 is A_2^i ,...,and x_m is A_m^i then

$$y^i = \sum_{j=1}^{m} p_{ij} x_j + p_{i0} . \tag{4}$$

where A_j^i , $j = 1,2,..., m$ represents a fuzzy set, x_j is the input variable, y^i is the output variable, $i \le c-1$,and, p_{ij} , p_{i0} are the real parameters to need be identified in the conclusion.

The Gaussian function is used for membership function of the fuzzy set, i.e.

$$M_{ij}(x_j) = \exp\left[\frac{-\|x_j - m_{ij}\|^2}{2\sigma_{ij}^2}\right]. \tag{5}$$

where m_{ij} and σ_{ij} are the center and width of the Gaussian membership function, respectively.

The last fuzzy rule R^c is:

R^c :if x_1 is A_1^c ,and x_2 is A_2^c ,...,and x_m is A_m^c then

$$y^c = b . \tag{6}$$

where b is the real parameters to need be identified in the conclusion.

The membership degree of the c-th fuzzy rule is all 1, i.e. $M_{c1}(x_1) = M_{c2}(x_2) = ... = M_{cm}(x_m) = 1$ .Then, the output of the TS fuzzy model can be obtained by the fuzzy weighted summation[24].

$$y(X)=\sum_{i=1}^{c-1}\left[\mu_i(X)\left(\sum_{j=1}^{m}p_{ij}x_j+p_{i0}\right)\right]+b\,. \tag{7}$$

where $\mu_i(X)=\prod_{j=1}^{m}M_{ij}(x_j)$, and stands for incentive strength of each rule in the former c-1 rules.

2) Parameter identification of TS fuzzy model

The parameter identification of the TS fuzzy model includes two parts: the antecedent part identification and the consequent part identification. Here, the antecedent part identification refers to the fuzzy rule extraction and the fuzzy parameter determination, and the consequent part identification refers to the identification of prediction model parameters. In this paper, the new antecedent part identification algorithm of TS model is proposed, which uses the phase space reconstruction technology to optimize the fuzzy input variable selection. The algorithm is described as follows.

Step1: determine the time series embedding dimension m and delay time τ. Extended the time series into m-dimensional phase space, denoted by

$$X(t)=[x_t,x_{t+\tau},\ldots,x_{t+(m-1)\tau}]\,. \tag{8}$$

where $t<N-(m-1)\tau$.

Step2: establish the relationship between the TS fuzzy model input vector and the single-step prediction output.

Let the input vector be:

$$\begin{bmatrix} X(1)\\ X(2)\\ \vdots\\ X(t)\end{bmatrix}=\begin{bmatrix} x_1 & x_{1+\tau} & \cdots & x_{1+(m-1)\tau}\\ x_2 & x_{2+\tau} & \cdots & x_{2+(m-1)\tau}\\ \vdots & \vdots & \vdots & \vdots\\ x_t & x_{t+\tau} & \cdots & x_{t+(m-1)\tau}\end{bmatrix}. \tag{9}$$

Then the single-step prediction output is

$$\begin{bmatrix} y(1)\\ y(2)\\ \vdots\\ y(t)\end{bmatrix}=\begin{bmatrix} x_{2+(m-1)\tau}\\ x_{3+(m-1)\tau}\\ \vdots\\ x_{t+1+(m-1)\tau}\end{bmatrix}. \tag{10}$$

Step3: input the first data point $X(1)$ produce the first fuzzy rule.

The fuzzy set parameter m_{1j}, σ_{1j} taken as $m_{1j}=x_{1+(j-1)\tau}$, $\sigma_{1j}=\sigma_{init}$, $j=1,2,\ldots,m$. σ_{init} is a preset Gaussian function width threshold.

Step4: the new input vector data $X(t)$ is received to determine whether a new fuzzy rule is generated. Calculate the incentive intensity of the existing rules for the new input vector data, that is $\mu_i(X(t))$, $i=1,2,\ldots,c(k)$, and $c(k)$ is the existing rule number, find the fuzzy rule corresponding to the maximum incentive intensity, denoted as I, and the corresponding incentive intensity value, denoted as μ_I.

If $\mu_I<\mu_{th}$, which indicates that the existing fuzzy rules do not support for the input data, and a new rule needs to be generated. Go to Step5 and determine the new rule parameters. Here, μ_{th} is the preset threshold, which is taken as 0.5.

If $\mu_I>\mu_{th}$, which indicates that existing fuzzy rules support new data, there is no need to generate new rules, Go to Step6 and the Gauss membership function center of rule I is updated directly.

Step5: calculate the parameters of the new fuzzy rule according to equations (11) and (12), and update the number of rules of the model.

$$m_{(c(k)+1)j}=x_{t+(j-1)\tau}\,. \tag{11}$$

$$\delta_{(c(k)+1)j}=\beta\left|x_{t+(j-1)\tau}-m_{c(k)j}\right|\,. \tag{12}$$

$$c(k)=c(k)+1\,. \tag{13}$$

where β is the overlap coefficient of two types of fuzzy spaces, generally value is 0.5, $c(k)$ is the total number of model rules.

Step6: the center of the Gaussian membership function of the I-th rule is updated according to equations (14) and (15).

$$m_{c_I j}=(m_{c_I j}\times a_I+x_{t+(j-1)\tau})/(a_I+1)\,. \tag{14}$$

$$a_I(k)=a_I(k)+1\,. \tag{15}$$

where $a_I(k)$ is the number of input vector data that the I-th rule contains at time k.

Step7: repeat from Step3 to Step6 until there is no the new input vector data.

After iterating repeatedly for the above algorithm, the antecedent part fuzzy rules of TS model and fuzzy rule parameters for the ECG signal can be identified. The algorithm effectively overcomes the subjectivity of traditional algorithms based on manual experience to set fuzzy input vector, which affects the accuracy of extracting fuzzy rules, and effectively improves the model identification effect.

The consequent part of TS model uses the regression model of standard linear support vector machine[25],which has:

$$\begin{aligned} y\,(X(t)) &= \sum_{i=1}^{c-1}\left[\mu_i(X(t))\left(\sum_{j=1}^{m}p_{ij}x_{t+(j-1)\cdot\tau}+p_{i0}\right)\right]+b \\ &= P^T O(t)+b \end{aligned} \tag{16}$$

where

$$P=[p_{10},p_{11},...,p_{1m},p_{20},p_{21},...,p_{2m},...,p_{(c-1)0},...,$$
$$p_{(c-1)1},...,p_{(c-1)m}]^T\in R^{(c-1)(m+1)}$$

$$O(t)=[\mu_1(X(t)),\mu_1(X(t))x_1,...,\mu_1(X(t))x_m,$$
$$\mu_2(X(t)),\mu_2(X(t))x_1,...,\mu_2(X(t))x_m,$$
$$...,\ \mu_{c-1}(X(t)),\mu_{c-1}(X(t))x_1,...,$$
$$\mu_{c-1}(X(t))x_m,]^T\in R^{(c-1)(m+1)}$$

Let the input vector data of ECG signal have $N1$, according to the above model, the consequent parameters p and b are solved by the training data $(O(1),y(1)),...,(O(N1),y(N1))$,where p_{ij} is:

$$p_{ij}=\sum_{k=1}^{N1}\alpha_k\mu_i(X(k))x_j\ . \quad (17)$$

where $i=1,2,...,c-1$, $j=0,1,2,...,m$, α_k is the Lagrange multiplier, and $x_0=1$.

D. Predictive precision index

To verify the proposed prediction performance, the Mean Absolute Error (MAE), Root Mean Squared Error(RMSE) and are employed. The MAE and RMSE are calculated by the following formula:

$$MAE=\frac{1}{N}\sum_{j=1}^{N}\left|\hat{y}_j(k)-y_j(k)\right|. \quad (18)$$

$$RMSE=\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left|\hat{y}_j(k)-y_j(k)\right|^2}\ . \quad (19)$$

where $y_j(k)$ represents the value of the desired output, $\hat{y}_j(k)$ represents predicted value, and N is equal to the number of predicted vectors.

III. RESULTS

A. Chaotic characteristic recognition of ECG signal

The experimental data come from the No.100, No.113 and No.119 sample data of the MIT-BIH standard ECG database. The sampling frequency of the sample data is f=360Hz, and taking 0~10s ECG data. the sample data of No.100 ECG signal is shown in Fig.1. The sampling point of the 10s ECG data is N=3600, and the sample time series is expressed as $\{x_1,x_2,...,x_{3600}\}$,Calculate the K entropy of the three sample data, as shown in Fig.2.

It can be seen from Fig.2 that the K entropy of three sample data of the ECG signal gradually decreases with the increase of the embedded dimension m, and finally remains unchanged, and all K are greater than 0, which fully demonstrates that the ECG signal has certain chaotic characteristics.

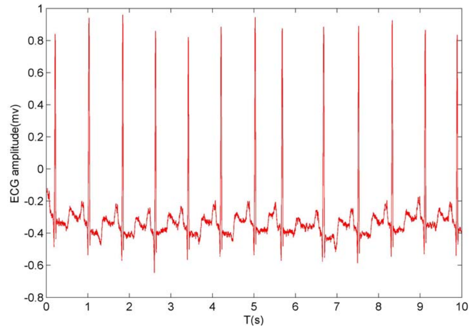


Figure 1. No.100 ECG signal

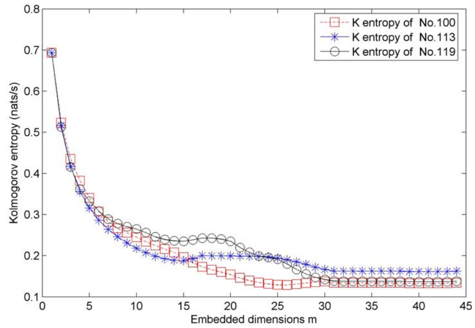


Figure 2. The K entropy of three ECG sample data

B. Analysis of embedding dimension m and delay time τ of phase space reconstruction for ECG signal

Determining the phase space reconstruction embedding dimension m for three ECG signal sample data by false neighbor method. The results are shown in Fig.3. It can be seen that the embedding dimension of No.100, No.113, and No.119 is greater than 13, 8 and 10, respectively, and the false neighbors are substantially less than 5%.To reduce the amount of computation in model identification process, the embedding dimension m is selected when the false neighbors are less than 5% in the paper. Then the m of three sample data is $m_{100}=13$, $m_{113}=8$, $m_{119}=10$, respectively.

The delay time of three ECG sample data is determined by the average displacement method. The results are shown in Fig. 4. It can be seen from Fig.4 that the average displacement of the three sample data and its slope change with the change of the delay time τ. When the slope of the average displacement reaches to 40% of its initial value for the first time, the corresponding delay time τ is marked with a circle in the Fig.4. Then the delay time of the three sample data is $\tau_{100}=0.0183$ s, $\tau_{113}=0.0139$ s, $\tau_{119}=0.0139$ s.

C. MG time series and ECG signal prediction

To prove the algorithmic validity based on TS fuzzy model of phase space reconstruction, the prediction of typical nonlinear Mackey-Glass(MG) time series is firstly performed, and compared performance with other prediction algorithm.

The Mackey-Glass series differential equation is defined by:

$$\frac{\partial x(t)}{\partial t}=\frac{ax(t-\tau)}{1+x^{10}(t-\tau)}\text{-}bx(t)\,. \qquad (20)$$

where $\tau=17$, $x(t)$ represents the concentration of blood at time t when the blood is produced, a and b are chosen as 0.2 and 0.1, respectively.

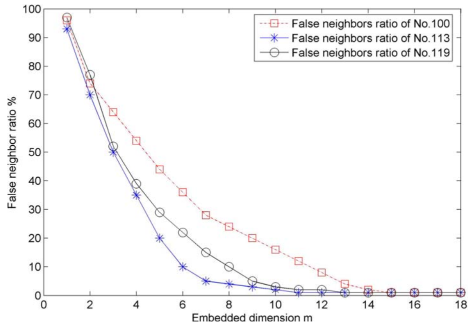
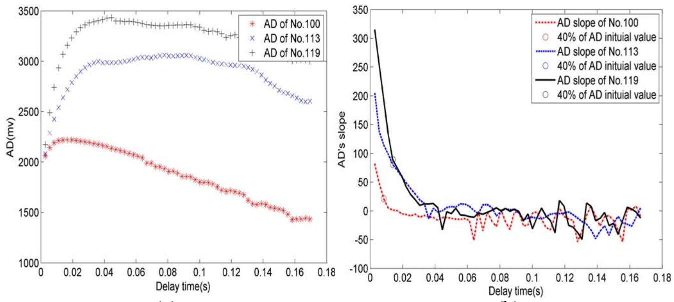


Figure 3. False neighbors change of sample data with the embedded dimension *m*



(a) (b)

Figure 4. AD and AD's slope of sample data with the delay time τ (a)AD (b)AD's slope

Suppose, the training data series are of length 500, followed testing data series of length 500, respectively. The prediction of testing data for MG series and the corresponding error curve as shown in Fig.5, the "+" marks represent the actual MG data, and the "•" marks represent the predicted output in the Fig.5. Obviously, the prediction of MG sequence is very satisfactory, and the normalization mean aquare error(NMSE) is 2.49 $\times 10^{-7}$, which is significantly lower than that of the literature[5-6]. Therefore, the proposed algorithm is highly effective for the prediction of nonlinear time series.

The 2500 data point of the reconstructed ECG signal is taken as the training sample data of the prediction model, and the ECG signal at the subsequent time point is predicted according to the identification result. The single step prediction is used in the prediction model.

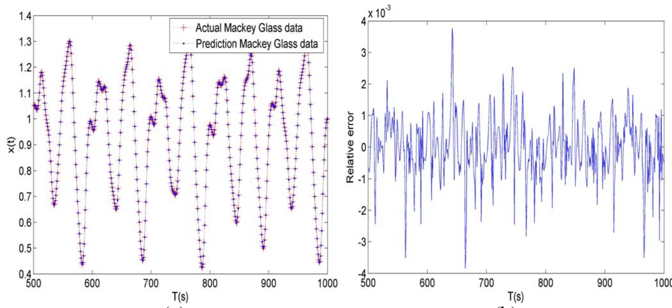
Then the input vector of No.100 data sample expressed as:

$$X(t)=\{x_{t+(m-1)*\tau},\ldots\}=\{x_{x_t,\ldots,x_{t+36}}\}.$$

where $t=1,2,\ldots,2500$, $m=1,2,\ldots,13$.

The output vector of model for the training sample is:

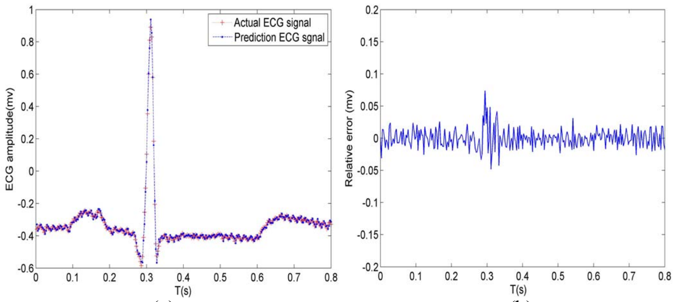
$$y(t)=x_{t+(m-1)\tau+1}=x_{t+37}\,.$$



(a) (b)

Figure 5. The prediction curve and error curve of MG series (a) The prediction curve of MG series (b) Prediction error curve of MG series

For No.100 ECG data sample, the prediction of any single cardiac cycle and the corresponding error curve as shown in Fig.6.The "+" marks represent the actual ECG data, and the "•" marks represent the predicted output in the Fig.6. Obviously, the predicted values fit well the raw data, and MAE is less than 0.0106. The predicted results of multiple cardiac cycle for No. 113 and No. 119 are shown in Fig.7. In the Fig.7, the "+" marks represent the actual ECG data, and the "•" marks represent the predicted output. The results show that the prediction of multi-cycle ECG signal also is better. The error indexes of this method compare with that of the traditional neural network method, as shown in Table Ⅰ. It can be seen that the predictive accuracy of the proposed algorithm is more higher than that of other methods.

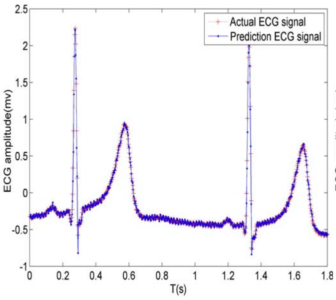


(a) (b)

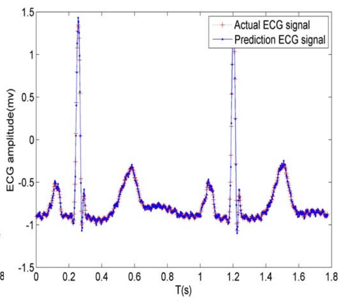
Figure 6. The prediction curve and error curve of any single cardiac cycle (No.100 data) (a) The prediction curve of any single cardiac cycle (b)Prediction error curve of any single cardiac cycle

IV. Conclusion

ECG signal can objectively reflect the working state of the heart system and provide important information for the prevention and diagnosis of heart disease. Predictive research on ECG signal has important potential applications in reducing data storage, restoring data and predicting disease, etc. The traditional prediction method firstly needs to establish the subjective model of the sequence and then proceed signal predicting, which inevitably adds the influence of human factors on the prediction accuracy of the model. In this paper, the TS fuzzy model is combined with the technology of phase space reconstruction, and the new forecasting method of ECG signal is put forward, which avoids the predictive person's subjectivity to some extent. The simulation results show that the proposed algorithm has higher estimate accuracy. However, some issues should be taken into consideration, such as optimizing the number of learning sample points and avoiding fuzzy rule disasters, etc, this method need to be further improved in practical application. In short, our proposed approach of ECG prediction would be a new idea for forecasting ECG signal with certain application prospects in ECG data processing and cardiovascular disease pre-diagnosis.



(a)



(b)

Figure 7. The prediction of multiple cycles ECG (a)No.113 prediction curve (b) No.119 prediction curve

TABLE I. ERROR INDEX OF DIFFERENT MODEL PREDICTION

method	sample	Error Performance Index	
		RMSE	*MAE*
method 1	100	0.0233	0.0157
	119	0.0423	0.0187
method 2	100	0.0423	0.0240
	113	0.0689	0.0421
This method	100	0.0146	0.0106
	113	0.0281	0.0172
	119	0.0231	0.0152

Note: method 1 is the neural network algorithm based on variational mode decomposition; method 2 is the neural network algorithm based on phase space reconstruction.

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