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A Novel Fuzzy Based Method for Heart Rate Variability Prediction

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ABSTRACT

In this paper, a novel technique based on fuzzy method is presented for chaotic nonlinear time series prediction. Fuzzy approach with the gradient learning algorithm and methods constitutes the main components of this method. The learning process in this method is similar to the conventional gradient descent learning process, except that the input patterns and parameters are stored in memory as a look-up table after upgrade. In the testing phase according to input patterns, the nearest neighbors and the weights corresponding to the test pattern, similar patterns are extracted from memory. Eventually, by extracted weights and input pattern, prediction is performed. In order to validate the proposed method for predicting, the Mackey-Glass, Lorenz and biological Heart Rate Variability (HRV) time series is used. Finally, the results of proposed method with the conventional methods of time-series prediction are also compared. The results demonstrate the capability of proposed method in chaotic time series prediction.
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1. INTRODUCTION

Analysis of natural convection found applications in thermal insulation, cooling of electronic devices, Chaos theory as an essential part of nonlinear dynamics is a good tool to show the characteristics of dynamic systems and the prediction of complex systems trajectories. The main feature of deterministic chaotic systems is their sensitivity to initial condition. In other words, a small difference at initial conditions leads to a major difference over time [1].

The chaos theory, as an essential part of nonlinear theory, has provided an appropriate tool to illustrate the characteristic of the dynamical system. There are four fundamental features for chaotic systems: a periodic that is the same state which will not be repeated, bounded meaning that neighbor states remain within finite range and does not approach infinity, deterministic that there is a governing rule with no random term to predict the future state of the system, and sensitivity to initial conditions meaning that a small difference in initial conditions (two point close to each other) will cause diverge as the state of system progress [2]. Due to rapid advances in chaos theory and its application in signal processing, communications, control, socio-economic and bio-informatics, modeling and predicting of chaotic systems has attracted many enthusiasts of the scientific community [3-5].

In many cases, an accurate analytical model for a complex system like the stock market and the network load is very difficult, because the structure of such systems is very complex and the data are inaccurate and incomplete. Although, the deterministic chaotic systems are often considered as unpredictable systems for their randomness aspects, but such systems can be predicted for short periods. Thus, starting from 1980, chaotic time series prediction has been a popular subject [6]. With the development of chaos theory, many methods have been proposed to predict the chaotic time series. Most of the proposed methods can be classified in two large groups: global and local. In global approach, the overall of time series can be modeled in terms of a mathematical equation.

The model is used in the whole phase space. Obviously, the disadvantage of this method is that the arrival of new information to systems may change all or part of the obtained parameters previously. Therefore, invalidate the previous model, and again a lot of time is

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required to re-estimate the model parameters. To overcome the aforementioned problem, in local model, only a portion of the attractor is used for time series prediction [7-10]. Therefore, a defect in global modeling methods, using locally have been more welcoming. Among the various types of local modeling techniques, neural and fuzzy techniques have been considered over other methods. Artificial neural network is a nonlinear device that mimics the human nervous system function [11]. These networks have the properties such as associative memory, self-organizing, data- driven and self-adaptive [11, 12]. Artificial neural networks can learn the patterns and can also detect hidden functional relationships between patterns. However, there is no mathematical model for information; so, to obtain such a relationship requires a lot of energy and cost [12]. In the training stage, the neural network is trained with algorithms which have been proposed in the various references. In the test phase with the new entrance to the system, the trained neural network produce the desired output [12-16].

Several types of artificial neural networks have been used to predict time series. Some examples have been used more than others in this area include: multilayer neural networks [17], neural networks [18-20] and neural network-based nonlinear autoregressive model with exogenous input (NARX) [21, 22].

Because of the good features of fuzzy logic to deal with imprecise and vague information, this method is widely used in the branches of engineering [23-25]. The ability of fuzzy logic is that it can translate the method and the logic of human decision making in the form of fuzzy rules. The use of vague and imprecise information in order to carry out the decision process has become the fuzzy model as an effective model for predicting. The most important issues facing the fuzzy system are how to determine membership groups, their number and type, the design of rules for the fuzzy decision process, and the scale function used in fuzzyfication and defuzzyfication functions.

Therefore, fuzzy models are widely used in forecasting time series [26, 27]. Anfis network proposed in 1993 by Jang has the advantages of both fuzzy and neural network approaches. Anfis uses rules and parameters related to train data for setting membership function [6, 28]. Other techniques have been cited in the references to predict time series. AI-based methods [29, 30], Self-organizing networks [31], support vector machines [32], wavelet networks [33] and methods based on delay embedding [34, 35] have been considered more than the other methods. The present paper is organized as follow: after introduction, the phase space reconstruction is presented concisely. The benchmark and HRV time series are demonstrated in section 3. In section 4, the performance of proposed method is investigated. Finally, the discussion and conclusion is stated in section 5.

2. PHASE SPACE RECONSTRUCTION

In this section, it is presented that how the phase space can be reconstructed from scalar time series by means of time lag embedding technique.

2. 1. Concept Many natural systems exhibit nonlinear or chaotic behavior in which by using chaos theory can be defined in terms of mathematical formulas. A chaotic time series in phase space is displayed as a vector space in R^n Euclidian space. Each point is described with an n-dimensional vector (t) in this space [36].

$$s(t) = \{s_1(t), s_2(t), \ldots, s_n(t)\} \tag{1}$$

where, t is the index of time series, in the phase space dimension and $s_i(t)$ is the dynamical system components. Based on the Tekken embedding theorem [37], since s(t) and its components in a chaotic system are unknown, if the value of a component or a variable x(t) of the dynamical system can be determined, then the attractor will be reconstructed [38]. In other words, if the value of x(t) is measurable and dynamic reconstruction of a chaotic system by y(t) according to Equation (2), then the system dynamics in reconstructed space is similar to the original attractor in terms of the geometry.

$$y(t) = \{x(t), x(t - T), x(t - 2T), \ldots, x(t - DT)\} \tag{2}$$

where, T is time lag. In the absence of system equations, chaotic time series is used for the reconstruction phase space. In such cases, by choosing a particular embedding dimension for time series, attractor can be reconstructed. By considering a chaotic time series x(t) in the phase space, the attractor can be reconstructed according to Equation (2), where D is the embedding dimension, and T is the time lag [39]. Parameters D and T are called reconstruction parameters.

2. 2. Time Lag The parameter T is very important in successfully reconstruction. T must be selected to provide minimum correlation among data in reconstructed phase space. If T is too short then coordinates x(t) and x(t+T) , … in Equation (2) are almost near to each other. So, all vectors in delay coordinate space are focus around the diagonal. Reconstruction is useless in this situation [40]. In fact, the distances between sampling point are so low that could not provide useful information about dynamic of the system. If T is selected too large, the points in delay coordinate space are so far from each other that seem uncorrelated. In this case, the mutual information is almost zero. Significant stretching and folding have been occurred, which considering the large amount of T, no logical relationship between the data in reconstruction phase space is found. The mutual information which is criterion of correlation between neighboring points x(t) and x(t+T), is given by Equation (3) [41].

$$I(T) = \sum_t p(x(t), x(t+T)) \log \frac{p(x(t), x(t+T))}{p(x(t)).p(x(t+T))} \quad (3)$$

where, p(x(t)) and p(x(t+T)) are marginal probability density function of neighboring points x(t) and x(t+T). p(x(t),x(t+T)) is joint probability density function too.

2. 3. Embedding Dimension

According to Taken theorem [37], embedding dimension should satisfy the condition: $m \geq 2d+1$. d in aforementioned equation is correlation dimension. In order to reconstruct original attractor, we have to embed time series in the space with large enough dimension. The parameter m is the size of embedding dimension. If it were not large enough, reconstruction would be impossible. If dimension is too large, the volume of unnecessary calculation will increase. There are some cases reported in literature where estimate the embedding dimension from a given time series data [11] e.g. non-intersecting trajectory approach. In accordance this method, if reconstruction attractor is large enough, trajectory does not cross itself. In 1983, another approach was proposed by Grassberger and Procaccia. At first, correlation function is calculated from Equation (4).

$$C(R) = \lim_{N \to \infty} \left[\frac{1}{N(N-1)} \sum_{j=1}^{N} H(R - |x_i - x_j|) \right] \quad (4)$$

where, x_i and x_j are attractor points which are selected randomly among reconstructed attractor points, H(y) is Heaviside function and N is number of points which are selected from total attractor space randomly. R and $|\ldots|$ are also the radius of sphere centered on x_i or x_j and ∞ -norm, respectively. For some ranges of R, correlation function and embedding dimension should satisfy linear relation as Equation (5).

$$d(m) = \frac{\ln(C(R))}{\ln(R)} \quad (5)$$

where, $d(m)$ is the size of embedding dimension. In this paper, we use the Grassberger-Procaccia algorithm to estimate the embedding dimension. First, select the initial embedding dimension then plot the ln(c(R))-ln(R) curve under different dimension, finally determine the graph of each d(m) value and estimate the slope, which is the correlation dimensiond(m).

3. PROPOSED METHOD

The proposed method uses fuzzy gradient descent learning algorithm, the nearest neighbor algorithm and delay coordinate technique for prediction of chaotic time series. The parameters embedding dimension and time lag are obtained from an observed time series firstly. Then, phase space has been reconstructed by these parameters. The number of fuzzy system inputs is considered as much as embedding dimension. Learning phase in this regard is similar to the conventional gradient descent method. After determining the reconstruction parameters, the overall structure of fuzzy system including fuzzification, defuzzification, membership groups and interference engine are specified. Product inference engine, singleton fuzzifier, center average defuzzifier, and Gaussian membership function have been used in this study. The Fuzzy system is formed as follows:

$$f(x) = \frac{\sum_{l=1}^{M} \bar{y}^{l} \left(\prod_{i=1}^{D} \exp\left(-\left(\frac{x_i - \bar{x}_i^{l}}{\bar{\sigma}_i^{l}} \right)^2 \right) \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{D} \exp\left(-\left(\frac{x_i - \bar{x}_i^{l}}{\bar{\sigma}_i^{l}} \right)^2 \right) \right)} \quad (6)$$

where, M is the number of fuzzy rules, D embedding dimension, x_i^{-1} the center of input membership functions, σ_i^{-1} width of Gaussians, x_i i^{th} input, and y^{-1} the center of output membership functions.

3. 1. Train Phase

At every stage of the training, reconstructed vector as input vector and next scalar point of time series are considered as the output of the fuzzy system. After applying the inputs to the fuzzy system, according to predetermined membership functions, the input value to each membership determined as follow.

$$\exp\left(-\left(\frac{x_i - \bar{x}_i^{l}}{\bar{\sigma}_i^{l}} \right)^2 \right) \quad (7)$$

where, i=1, 2, …, D, x_i^l and $б_i^{-1}$ are center of membership functions and width of the membership function per rule, respectively. Then, according to Equations (9) and (10), X and Y are obtained by summation operator and weighted summation operator.

$$\bar{z}_l = \prod_{i=1}^{D} \exp\left(-\left(\frac{x_i - \bar{x}_i^{l}}{\bar{\sigma}_i^{l}} \right)^2 \right) \quad (8)$$

$$X = \sum_{l=1}^{M} \bar{y}^{l} \bar{z}_l \quad (9)$$

$$Y = \sum_{l=1}^{M} \bar{z}_l \quad (10)$$

Although the structure of the fuzzy system is selected as Equation (6), but fuzzy system has not been designed, because the parameters y^{-1} ، x_i^{-1} and σ_i^{-1} are not determined and distributed randomly. In order to determine the exact value of the parameters, we need an error function. Therefore, the square error function defines as Equation (11).

$$e = \frac{1}{2}(f - y)^2 \tag{11}$$

where, f and y are fuzzy and scalar outputs of time series, respectively. In each step of prediction, training error is calculated by Equation (11). The result has been compared to predetermined value that considered as the error bound previously. If the error is greater than predetermined value, the parameters are changed in an internal loop to reduce error. For each pattern, the training process stopped when the iteration or error reaches to predetermined value. Then, this process is repeated for the next patterns. The update equation is as follows:

$$\bar{y}^{l}(q+1) = \bar{y}^{l}(q) - \alpha \left.\frac{\partial e}{\partial \bar{y}^{l}}\right]_q \tag{12}$$

$$\bar{x}_i^{l}(q+1) = \bar{x}_i^{l}(q) - \alpha \left.\frac{\partial e}{\partial \bar{x}_i^{l}}\right]_q \tag{13}$$

$$\bar{\sigma}_i^{l}(q+1) = \bar{\sigma}_i^{l}(q) - \alpha \left.\frac{\partial e}{\partial \bar{\sigma}_i^{l}}\right]_q \tag{14}$$

where, q, e, x_i^{-l} , y^{-l} and σ_i^{-l} are the number of the internal loop iteration, error, center of Gaussian membership functions, output membership center and width of Gaussian membership groups, respectively. For convenience and increase training speed, y^{-l} is only considered as variable. Parameters x_i^{-l} and σ_i^{-l} are fixed. Using chain rule, the training algorithm for y^{-l} is obtained as follows [42]:

$$\bar{y}_i^{l}(q+1) = \bar{y}_i^{l}(q) - \alpha \frac{f - y}{Y} \bar{z}_l \tag{15}$$

where, q is the number of the internal loop iteration and α is learning rate that they are considered 30 and 8, respectively. Y and z_i^{1} are also calculated according to Equations (10) and (8). In this study, the width of the Gaussian membership groups σ_i^{-l} is considered as much as 0.4. x_i^{-l} Set could also be uniformly distributed between maximum and minimum of each entry. Here, the range between maximum and minimum per input is divided into four equal parts.

In training phase, for each pattern from training matrix, y^{-l} set has been initially randomly distributed. In order to minimize error function, y^{-l} set is changed. Then, both fine-tuned y^{-l} and input vectors are stored in a memory. This process will be repeated for the next pattern from input matrix.

3. 2. Test Phase The test pattern that used to examine prediction performance of proposed method is selected from test space. Pattern that has a closet distance to it (test pattern) is selected from memory. The distance can be Euclidean distance or any other distance. Then corresponding weight that stored in memory, are extracted too. Prediction will be done by means of extracting weight and test pattern. This process is repeated for all testing set. The proposed scheme is different from standard training method like gradient. Here, both input pattern and correspond weight are stored in the memory at training stage. At testing stage, the nearest pattern to test pattern, which stored in the memory, is selected firstly and then the correspond weight are extracted from memory too. The extracting weights are put on the network to do the prediction. In conventional methods, the weights of the network are modified during the training phase but in test phase, they are fixed. Therefore, changing the weight of the network in each step of prediction is the main difference between proposed scheme and conventional methods. The proposed method has been tested on both benchmark time series Mackey-Glass and Lorenz. Then, the prediction performance of proposed method is compared with conventional method in chaotic time series prediction. In order to more evaluation, the proposed scheme has been adopted to predict real life HRV time series data. The simulation results show that the new scheme has satisfactory performance in context of HRV prediction.

4. BENCHMARK TIME SERIES

To evaluate the proposed method, the famous Mackey-Glass and Lorenz time series as well as biological HRV time series is used. In this section, these three time series are studied briefly.

4. 1. Lorenz Equation A popular example of a chaotic time series is related to climate change. Lorenz model is obtained by simplifying Navier-Stokes equation that is used in fluid mechanics. Lorenz model is not a good approximation to the original equations, because, except for certain range of parameters the model is not interesting and for changing parameters, regions of chaos has been observed [43]. Lorenz equations are given by:

$$\begin{aligned} \frac{dx(t)}{d(t)} &= \delta[y(t) - x(t)] \\ \frac{dy(t)}{d(t)} &= x(t)[r - z(t)] - y(t) \\ \frac{dz(t)}{d(t)} &= x(t)\,y(t) - bz(t) \end{aligned} \tag{16}$$

where, x,y and z are the real function of time and б , b and r are dimensionless parameters. In this paper, x-coordinate is considered as a chaotic time series and б, b and r, are chosen 10, 8/3 and 28, respectively.

4. 2. Mackey-Glass Equation The Mackey-Glass system has been introduced as a model of white blood cell generation [44]. Because of Mackey-Glass chaotic characteristics, is used as a benchmark in literature. The time series is generated by differential equation as follow.

$$\frac{dx(t)}{d(t)} = \frac{ax(t-T)}{[1+x(t-T)^c]} - bx(t) \tag{17}$$

where, T is the time lag and a, b and c are dimensionless parameter which are usually considered as 0.2, -0.1 and 10, respectively. T changes in above equation create the different type of attractors. For T<4.43 fixed-point attractor is created, one stable limit cycle produce when 4.43<T<13.3 and two limit cycle when 13.3<T<16.8. Chaos is observed when T>16.8 [41]. In this paper a, b and T are taken as .2, -0.1 and 17, respectively. The initial value for x(0) is 0.8 too.

4. 3. HRV Time Series Herat rate variability is the variation of beating interval in cardium. This is also called R-R interval. R is the peak of Electrocardiogram (ECG) time series, which demonstrate the vascular contraction. Low and high of HRV and its variation has significant clinical indicators and are caused because of muscle cramps, acute heart failure, and emotional arousal. Biological signals such as EEG, ECG, and HRV are classified in non-stationary signals [45]. However; the chaotic nature of such signals is controversial among researchers. In some references, such signals have been classified among the chaotic signals [46, 47]. Nevertheless, others have not [45, 47]. They all agree on the non-stationary behavior of such signals [48, 49]. However, due to the complex nature of the signal, they are used as a difficult benchmark to evaluate the ability of the proposed method in literature [50-52]. In this paper, the HRV is used to evaluate and validate the proposed method for time series prediction. Error of prediction is calculated by three criteria: MSE, RMSE, NMSE (Equations (18)-(20)).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{18}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{19}$$

$$NMSE = \frac{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{20}$$

where, $y_i, \hat{y}_i, \bar{y}$ are mean, predicted value, and time series, respectively and N is the number of predicted points.

5. TIME SERIES PREDICTION USING PROPOSED METHOD

In this section, the performance of proposed method is evaluated by applying to three benchmark time series. In order to show the complexity, largest Lyapunov exponent for Lorenz, Mackey Glass and HRV time series are calculated using TSTOOl[1] and their value are obtained as +0.45, +0.0116 and +2.1, respectively. The greater lyaponuv exponent, the higher complexity and the shorter predictability.

5. 1. Prediction of Lorenz Time Serie To generate Lorenz time series, the Equation (16) is simulated with initial condition 1, 3, 4 for x, y, z, respectively.

The vector x is selected with 7500 points. Of these, 4,000 points will be assigned as the training vector. Then, according to Equations (4) and (3), the time lag and embedding dimension are obtained 3 and 3, respectively. Four membership functions are considered for each input. Membership functions have Gaussian distribution. The numbers of rule are achieved as 64 according to the number of input membership functions. The prediction result and its error are illustrated in Figure (1) and Table. 1.

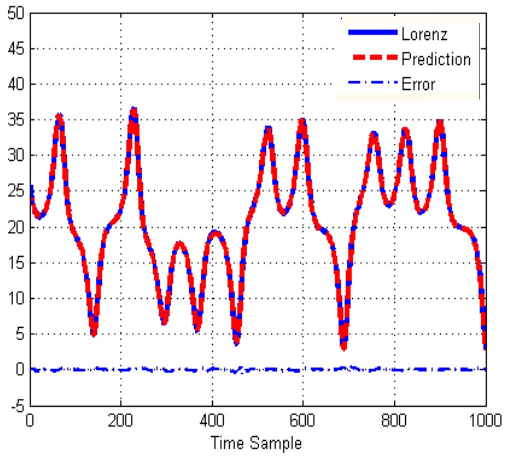

Figure 1. One step ahead prediction of Lorenz time series using proposed method. Original time series, predicted value and prediction error

[1] Tstool v 1.11, http://www.physik3.gwdg.de/tstool

TABLE 1. Results of Lorenz chaotic time series prediction by different methods .

Time Series	**Lorenz**		
Error	**MSE**	**RMSE**	**NMSE**
MLP_Gradiant	0.9	9.5E-1	1.9E-2
TS_Fuzzy	1.0E-5	3.3E-3	1.7E-7
LPC(5)	9.1E-3	9.5E-2	1.5E-4
AR(4)	0.4	6.3E-1	6.8E-3
Fuzzy_Gradiant	0.2	3.3E-1	1.0E-3
Proposed method	4.9E-5	7.1E-3	2.8E-4

TABLE 2. Results of Mackey-Gladd chaotic time series prediction by different methods commonly used for prediction and proposed method

Time Series	**Mackey-Glass**		
Error	**MSE**	**RMSE**	**NMSE**
MLP_Gradiant	4.5E-3	6.7E-2	5.4E-2
TS_Fuzzy	4.5E-9	6.7E-5	5.5E-8
LPC(5)	1.7E-4	4.2E-3	2.1E-4
AR(4)	3.9E-1	6.3E-1	8.1E-1
Fuzzy_Gradiant	1.1E-2	1.0 E-1	4.2E-3
Proposed method	4.5E-3	6.7E-2	5.4E-2

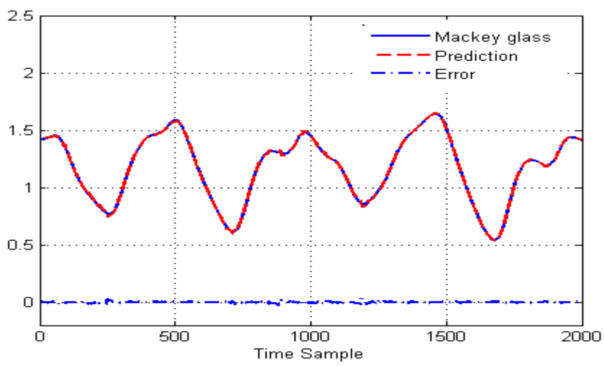

Figure 2. One step ahead prediction of Mackey-Glass time series using proposed method. Original time series, predicted value and prediction error.

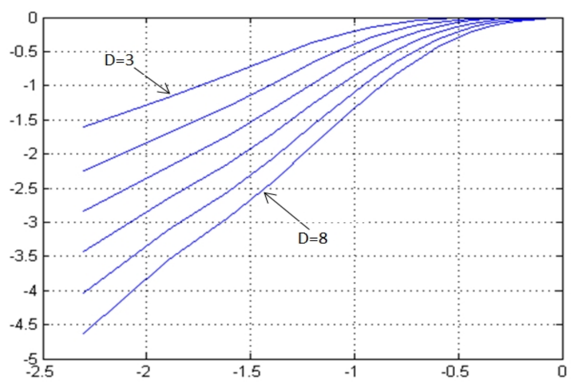

Figure 3. Determining embedding dimension through G-P algorithm

5. 2. Prediction of Mackey-Glass Time Serie

Proposed method is applied to Mackey-Glass time series and the result is illustrated in Figure (2).

To generate the time series, the Equation (17) is simulated with .2 as initial condition. The embedding dimension and time lag is achieved as 3 and 8, respectively. The train vector is considered as 4000 points and the test vector equal to 200 points. The number of fuzzy system set equal to three and four membership functions are assumedfor each input. Overall, the numbers of fuzzy rules are 64.

As shown in Figure 2 , very small prediction error shows the high performance of proposed method in time series prediction. In order to compare the proposed method with other methods used to predict chaotic time series, similar simulations, in the same conditions, are also executed by conventional methods whose results are presented in Tables 1 and 2.

The results in Table 2 indicate the better predictions of the proposed method in comparison with other methods. However, as can be seen in Tables 1 and 2, the proposed method performance is weaker in dealing with the Mackey-Glass and Lorenz systems than the TS fuzzy approach. Perhaps one of the reasons for this can be seen as a set of incorrect parameters. Another reason which can be outlined for this is the use of gradient learning algorithm, in contrast to other methods such as Levenberg-Marquardt, Gauss- Newton and ... algorithm that is considered to be weak. In addition, undesired local minimum, which is common in Gradient based method, can be considered as an additional problem. Using Mamdani fuzzy systems, number of training patterns to fuzzy system, the learning rate parameter and the number of iterations of the inner loop fuzzy systems are also the reasons for the poor performance of the proposed method against TS fuzzy approach.

5. 3. Prediction of HRV Time Serie

HRV time series is a very complex biological time series and most methods are failing to predict it. In this section, to further evaluation of the proposed method, the non-stationary HRV series prediction is studied. Figure 3 shows finding of embedding dimension based on Grassberger-Procaccia(G-P) algorithm. As can be seen in Figure 3, the slopes of graphs are constant after four. Therefore, the embedding dimension is chosen equal to four. The time lag is obtained four by using the mutual information method. HRV time series data is taken from MIT-BIH database [53]. HRV time series prediction results by the proposed method are presented in Figure 4. As can be seen in the figure, the fuzzy system is able to forecast the time series of HRV. In order to compare the proposed method with other methods, similar simulations, are also performed by conventional methods whose results are presented in Table 3. It can be seen from Figure 4 that the proposed method can predict HRV time series with a good accuracy. As it is shown in Table 3, other conventional methods of delaing with HRV signal in contrast with proposed method, , have poor performance. It is acquired from Table 3 that the proposed method has predicted better than the other methods even TS. The time lag and embedding dimension have been chosen equal to four to predict HRV. Different methods are presented in various references for these parameters calculations [29, 54, 55] but none of these techniques have claimed that they have been able to offer the best time lag and dimension for a time series [56]. Since the deterministic method for finding the optimal time lag and embedding dimension does not exist and also to ensure the accuracy of the proposed method ability to predict the time series, prediction using different dimensions and lags was carried out by proposed method. The obtained results are given in Table 4.

TABLE 3. Results of HRV time series prediction by different methods commonly used for prediction and proposed method

	MSE	RSME	NMSE
MLP_Gradiant	1.8E-2	1.3E-1	1.2
TS_Fuzzy	7.8E-3	8.9E-2	1.1
LPC(5)	2.7E-2	1.6E-1	2.8
AR(4)	4.3E-1	6.5E-1	1.0
Simple Fuzzy	1.1E-2	1.1E-1	1.2
Proposed method	7.1E-5	5.4E-3	1.1E-2

TABLE 4. The result of prediction of HRV with various time lags and dimensions

Embedding dimension	Delay Time	Number of Fuzzy Rule	Running Time (s)	MSE
3	8	64	6.75	1.8E-4
4	4	256	26.75	7.1E-5
5	2	1024	89.56	1.9E-4
6	1	4096	373.50	1.7E-4

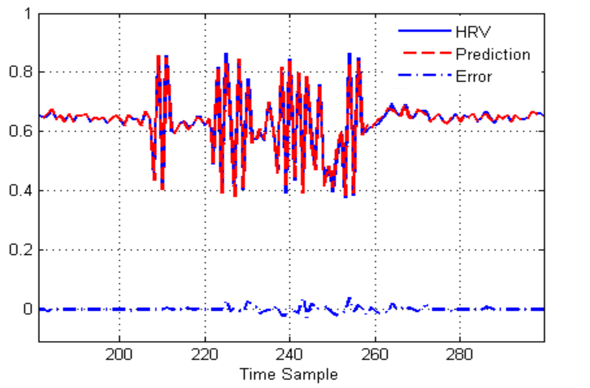

Figure 4. One-step ahead prediction of HRVtime series using proposed method. Original time series, predicted value and prediction error

As can be seen in the Table 4, the results are not very different from each other for various time lags and dimensions. However, the lowest error is obtained for dimension and time lag equal to four. The lack of much dependency of proposed method on the reconstruction parameters is another reason of the ability of the proposed method in time series prediction.

From the perspective of processing speed and computing complexity, the proposed method is somewhat slower than other methods and also more complex. This is because in the proposed method weights are fetched according to the input from memory, while in the other mentioned methods they are fixed. Constant weight, increase speed and reduce the complexity of the process, but greatly reduces the prediction accuracy. In this paper, by paying very little cost, we have greatly increased the accuracy of prediction.

6. DICUSSION AND CONCLUSION

In this paper, a new method is proposed for chaotic time series prediction. Phase space reconstruction and fuzzy technique with gradient-based training algorithm are components of the proposed scheme. Storing the input pattern and conventional weight in a memory and changing the weights of the network in each step of prediction can be considered as the main difference between our method and other conventional methods. Thus, a history of original system patterns and the fuzzy decision for each pattern are always available in the memory. Storing input pattern and correspond weight in a memory play an important role in increasing the prediction accuracy because there is quasi-periodic property in chaotic time series. If the training matrix is rich enough, the prediction ability will be considerably increased.

The neighboring relations of the scalar time series have been used for prediction in conventional methods such as artificial neural network, etc. Finally, the network weights, which are unchanged in test stage, are obtained from these relations. However, in proposed method, by similarity between test pattern and patterns, which were stored in the memory, correspond weights are also extracted from it (memory). Therefore, the network weights can be change during the test process. When the dimension value of the dynamical system is raised, consequently the number of both fuzzy rule and the parameters are increased. Training time will also increase. An obvious disadvantage in this situation, which the dimension is very high, is that the proposed method converge at a lower speed, which cannot satisfy the request of online prediction.

The proposed method has been used to forecast chaotic benchmark time series such as Lorenz map and Mackey-Glass. Prediction result were compared with the conventional methods such as TS-Fuzzy, Artificial neural network with gradient based learning algorithm and etc. simulation results demonstrate the superiority of the proposed method in comparison with other traditional methods. In some cases (Tables 1 and 2), it was observed that the proposed method has poor performance than TS-Fuzzy method. Poor convergence, undesired local minimum, determination the optimal parameters of the membership functions such as center and width, which in this study is determined by trial and error, could be considered as a main reason for malfunction of proposed method. In other to more evaluation, the proposed scheme has been used to real life HRV time series forecasting. The result is also compared with the conventional method especially TS-Fuzzy method. The result demonstrates that proposed model has a good prediction performance for HRV forecasting compared with the result of the other conventional methods such as TS-Fuzzy.

In this paper, the fuzzy system including center of membership functions and training rate are determined through trial and error. Using optimization techniques and evolutionary algorithms to optimize these parameters and apply other more powerful training methods such as Luneburg, it could be considered as two extension of proposed method to make prediction more efficient.

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A Novel Fuzzy Based Method for Heart Rate Variability Prediction

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چکیده

در این مقاله یک روش جدید بر مبنای روش فازی در پیش‌بینی سری‌های زمانی غیرخطی آشوبی ارائه می شود. روش فازی با الگوریتم آموزش گرادیان و روش نزدیکترین همسایه اجزای اصلی این روش را تشکیل می دهند. فرآیند آموزش در این روش همانند روش متداول گرادیان نزولی است با این تفاوت که الگوی‌های ورودی و پارامترها بعد از بهنگام سازی در یک حافظه جانبی بصورت جدول جستجو ذخیره می شوند. در مرحله ی تست با توجه به الگوی ورودی، نزدیکترین همسایه به آن و وزن‌های متناظر با الگوی متشابه با الگوی آزمون از حافظه جانبی استخراج می گردد. سرانجام توسط وزن های استخراجی و الگوی ورودی پیش‌بینی انجام می شود. روش پیشنهادی به منظور اعتبارسنجی برای پیش-بینی سری‌های زمانی مکی گلاس و لورنز و همچنین سری زمانی زیستی HRV مورد استفاده قرار می گیرد. در انتها نتایج روش پیشنهادی با روش‌های متداول در پیش بینی سری زمانی نیز مقایسه می گردد. نتایج بدست آمده بیانگر توانمندی روش مذکور در پیش‌بینی سری‌های زمانی است.

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