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ORIGINAL RESEARCH

A high efficient next generation reservoir computing to predict and generate chaos with application for secure communication

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Abstract

In this work, a high efficient next generation reservoir computing (HENG-RC) paradigm that adopts the principle of local states correlation and attention mechanism is proposed, which is able to process dynamical information generated by both the low dimensional and very large spatiotemporal chaotic systems (VLSCS). From a dynamical system perspective, the dynamical characteristics such as density distribution, Poincaré plots and max Lyapunov exponents of the proposed HENG-RC are studied. It is revealed that the trained model can be seen as a data-driven chaotic system. Furthermore, a novel scheme of secure communication based on chaotic synchronization of two HENG-RC systems is designed, of which the security is enhanced as the intruder needs to know simultaneously the training signal and details of the parameter setting in the HENG-RC. The digital implementation using field programmable gate array is experimentally realised, proving the feasibility of the secure communication scheme.

1 | INTRODUCTION

The incorporation of machine learning based approaches into the field of communication is of great significance[1–3]. The reservoir computing (RC), as a new kind of recurrent neural network (RNN)[4], is deemed as a best-in-class machine learning platform for processing data generated by various types of dynamical systems [5–10]. Specifically, the explicit expression between memory capacity and forecasting ability of a recurrent network including RC was studied. The RC scheme realised by random topological magnetic textures was proven to be capable of processing data even faster. The RC trained by the Tikhonov least squares regression was revealed to be capable of conducting high efficient prediction tasks. So far, various RC models have been proposed. These include double-reservoir echo state network (DRESN) [11], broad echo state network (BESN) [12], hierarchical delay-memory echo state network (HDESN) [13], integer echo state networks (intESN) [14] etc. Particularly, Appeltant et al. introduced a special architecture of RC that only used a single dynamical node with delayed feedback, i.e the time-delay reservoir (TDR)[15]. Based on TDR computing, a few modified models such as deep TDR computing were also developed [16–18]. Vastly different from the above-mentioned RC models, very recently, a brand new type of RC which used nonlinear vector autoregression (NVAR) for constructing a feature vector to replace actual reservoir was newly proposed [19, 20]. The paradigm released the requirement for optimising a multitude of metaparameters as in traditional RCs and showed an excellent performance at reservoir computing benchmark tasks such as forecasting, reproducing and inferring unseen data/behaviour of a dynamical system, and was claimed to herald the next generation of reservoir computing (NG-RC). However, it is still limited for studying the low dimensional chaotic systems. If the NG-RC is applied for very large spatiotemporal chaotic systems (VLSCS), a predictable problem arising is that the computing expense will become extremely high, as the VLSCS brings a huge amount of terms into the feature vector construction process. Therefore, the advanced technique requiring minimal computing resources, together with holding the functionality of dealing with a wide range of dynamical systems with a high efficiency, particularly for the VLSCS, are highly desired.

In this work, we firstly postulate a HENG-RC with feature vector constructed by adopting the principle of local states correlation. The principle describes the local nature of interactions between neighbouring states in spatiotemporal domain of a dynamical system, and can be effectively employed for predicting spatiotemporal time series[21, 22]. Compared with the NVAR, the construction of feature vector using this principle can eliminate many redundant terms for extracting the feature of dynamical time series, which reduce the computational expense greatly. More importantly, in the training process we introduce the attention mechanism that can enhance the prediction ability as well as increasing the efficiency. Numerically, we take Lorenz system and Kuramoto–Sivashinsky (KS) equation, as low-dimensional and VLSCS examples, respectively, to verify the effectiveness of the proposed model. The high efficiency, in particular for dealing with VLSCS is emphasised, and comparisons regarding to the traditional RC and the latest NG-RC are given in detail.

To evaluate the dynamical characteristics of an RC paradigm is significant for practical application exploration. Here, we further conduct the dynamical analysis of the HENG-RC. It is found that the HENG-RC after being trained exhibits dynamical characteristics. This evokes the secure communication application based on chaotic synchronisation. We, then, conceive the secure communication scheme that is based on chaos synchronisation of two HENG-RCs in parallel, which is simple and characterised by high reconfigurability in choosing encrypting chaotic systems, i.e. the HENG-RC can learn whatever types of chaotic systems and then behave like a real one, lifting the need for setting continuous chaotic systems as in traditional secure communication schemes [23–26]. The security of the scheme is high as the intruder needs to know simultaneously both the training signal and parameter setting details of the employed HENG-RC. The digital implementation of the scheme is experimentally conducted, which can prove the feasibility of the scheme.

To the best of our knowledge there is few work so far to design a reliable as well as with high security secure scheme by incorporating NG-RC. Though the work in [27], reported a secure communication scheme using traditional RC for replacing the receiver. In their design, the encryption systems cannot be set arbitrarily. In addition, the realisation of their scheme is limited by optical means. The work is structured as follows. The working principle of the proposed HENG-RC is introduced in Section 2. Numerical simulations of the HENG-RC using Lorenz system and KS equation, as low-dimensional and VLSCS examples, respectively, are conducted and compared with other RC models in Section 3. The dynamical analysis of the proposed HENG-RC is given in Section 4. The secure communication scheme together with its hardware experiment is presented in Section 5. Finally, the conclusion is presented.

2 | METHOD: MODEL CONSTRUCTION

We first briefly describe the working principle of the NG-RC recently developed in [20]. It uses the NVAR to replace the conventional reservoir [19]. The NG-RC creates a feature vector using input data at states of time t and number of time-delay states (k) with respect to t. Assuming a three-dimensional vector $u(t)$ composed of $X(t)$, $Y(t)$ and $Z(t)$ with time t in discrete as input signal, the feature vector consists of two parts: linear and nonlinear. The linear part is composed of the input vector from time t to $t-k$ ($k = 1, 2, \ldots$), and the nonlinear part is composed of the outer product of the linear vector. The mathematical process for feature construction can be described by:

$$S = S_c \oplus S_l \oplus S_{nl}, \tag{1}$$

$$S_{nl}^{p} = S_l \otimes S_l \ldots \otimes S_l. \tag{2}$$

In Equation (2) $S_l^k(t) = u(t) \oplus u(t-1) \ldots \oplus u(t-k)$, $\oplus$ represents the vector concatenation operation, $\otimes$ represents the outer product operation and p is the number of outer product operation. S_c is a constant vector, S_l^k and S_{nl} represent the linear and nonlinear part vector, respectively. k denotes the number of time-delay states.

There are two phases: training and predicating, included in the operation of NG-RC. In the training phase, the output weight matrix is adjusted via a regularised linear least-squares optimisation procedure, which can be expressed as [28]:

$$W_{out} = YS^T(SS^T + \lambda I)^{-1}, \tag{3}$$

where Y is the output we desired ($u(t+1)$), I is an identity matrix and λ is ridge parameter to prevent over-fitting. After training, the W_{out} is fixed, and one can let the output vector Y' feed back into input layer, the reservoir computer can automatically run itself for generating future states, i.e. the predicating phase. And in the predicting phase, the output vector is calculated by multiplying the $S(t)$, and the output weight matrix W_{out}, i.e.:

$$Y' = W_{out} \times S. \tag{4}$$

However, this type of NG-RC has a high computational expense, especially when dealing with VLSCS, as the feature construction procedure generates so many non-linear terms. In order to make the NG-RC more efficient as well as to maintain an excellent performance, an HENG-RC adopting the principle of local states correlation is proposed here, i.e. instead of using outer product of all linear states in linear vector, we, based on local states correlation, consider only the products of the neighbouring linear states to form the nonlinear part of the feature vector. The general architecture is given in Figure 1.

Specifically, assuming a general input that has Q-dimensions as shown in Figure 1, the overall nonlinear part S_{nl} is divided into k individual parts if there are k time-delay states considered: S_{nl}^{j} ($j = 1, 2 \ldots k$). Each of S_{nl}^{j} is further divided to Q sub-vectors S_{nl}^{ji}, which corresponds to the dimension number of the input vector. The S_{nl}^{ji} is composed of the products between $H_i(t-j)$ and the three neighbouring dimensional states $(i-1, i, i+1)$ in input vector at time $t-j$ and time $t-j-1$, i.e. : $H_{i-1}(t-j), H_i(t-j), H_{i+1}(t-j), H_{i-1}(t-j-1), H_i(t-j-1), H_{i+1}(t-j-1)$. Mathematically, the construction process for the nonlinear part of feature vector can

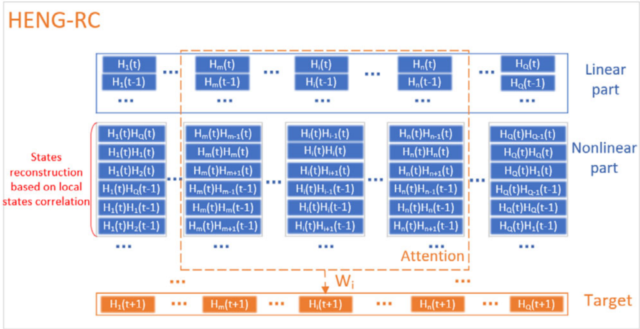

FIGURE 1 The architecture of the proposed HENG-RC with incorporating attention mechanism. The yellow dotted box indicates the region in feature vector where the attention mechanism is applied

be expressed as:

$$S_{nl} = S_{nl}^{1} \oplus S_{nl}^{2} \ldots \oplus S_{nl}^{k}, \tag{5}$$

and

$$S_{nl}^{j} = S_{nl}^{1j} \ldots \oplus S_{nl}^{ji} \oplus \ldots S_{nl}^{Qi}, \tag{6}$$

with

$$\begin{aligned} S_{nl}^{ji} &= H_i(t-j) \times H_{i-1}(t-j) \\ &\oplus H_i(t-j) \times H_i(t-j) \\ &\oplus H_i(t-j) \times H_{i+1}(t-j) \\ &\oplus H_i(t-j) \times H_{i-1}(t-j-1) \\ &\oplus H_i(t-j) \times H_i(t-j-1) \\ &\oplus H_i(t-j) \times H_{i+1}(t-j-1). \end{aligned} \tag{7}$$

It can be seen that the terms in the nonlinear part for constructing the feature vector is $Q \times 5 \times k$, while the number in original NG-RC is $(Q \times (k+1)+1) \times (Q \times (k+1))/2$. The computational expense is therefore lowered.

To increase the prediction performance as well as the efficiency, for the first time we introduce the attention mechanism for training the proposed HENG-RC. As indicated by the yellow dash box in Figure 1, each row, $i \in [1, Q]$, of output weight matrix W_{out} is trained independently with attention on neighbouring dimensions $(m, i-1, \ldots, i, i+1, ..n)$, where the m and N decide the attention range. The training process can be expressed by:

$$W_{out} = W_1 \oplus W_2 \oplus \ldots \oplus W_Q, \tag{8}$$

with

$$\begin{aligned} W_i &= Y_i(L_i)^T[L_i(L_i)^T + \lambda I]^{-1} \\ L_i &= S_{nl}^{jm} \oplus S_l^{jm} \ldots \oplus S_{nl}^{jn} \oplus S_l^{jn}, \end{aligned} \tag{9}$$

where Y_i is the ith-dimension of the expected output Y, L_i is the linear and non-linear states neighbouring the ith-dimension, and S_l^{jm} is the mth-dimension of input at time $t-j$. Note that $i-m = n-i = b$, b is the number of neighbouring dimensions involved in attention. The prediction ability of low-dimensional chaotic system and VLSCS are verified, respectively, in the following section.

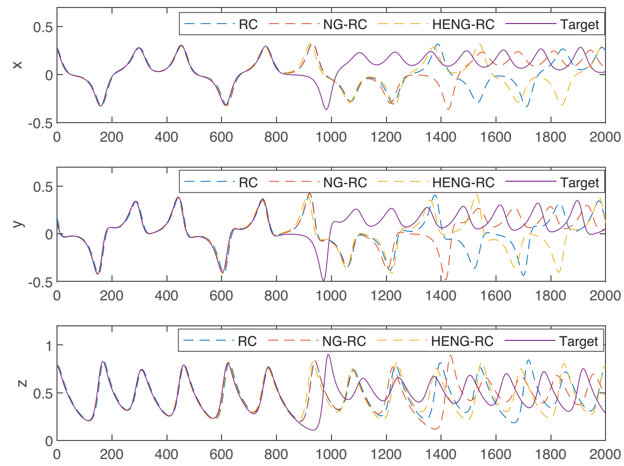

FIGURE 2 Prediction for x, y and z-dimensional time series of chaotic Lorenz system using HENG-RC is verified, and the prediction performance is compared between three models: RC, NG-RC and the proposed HENG-RC. The training data length for RC is 800 while for HENG-RC is 400

3 | RESULTS AND DISCUSSIONS

3.1 | Low-dimensional chaotic system: Lorenz equation

We first use the Lorenz equation as an example of low-dimensional chaotic system to train the proposed HENG-RC. The model of Lorenz equation is expressed as [29]:

$$\begin{aligned} \dot{x} &= \sigma(y-x), \\ \dot{y} &= \gamma x - y - xz, \\ \dot{z} &= xy - \beta z. \end{aligned} \tag{10}$$

where $\sigma = 10$, $\gamma = 28$ and $\beta = 8/3$, and in such a parameter setting the system works in chaotic state. The training data can be easily established using standard Runge–Kutta method, during which time steps in transient state should be discarded. The HENG-RC is then trained according to the procedure described in last section. The prediction results of in x, y and z-dimensions based on HENG-RC are given in Figure 2. To compare, we also calculate the time series prediction using traditional RC and the original NG-RC. From Figure 2, it can be seen that the proposed HENG-RC works comparably with the traditional RC as well as the NG-RC. But to achieve such a result the HENG-RC requires much less training data than RC. To be specific, we only used 400 time steps for training HENG-RC while it is 800 time steps for RC with 2000 neurons. Referring to the comparison with the NG-RC, it should be mentioned that the

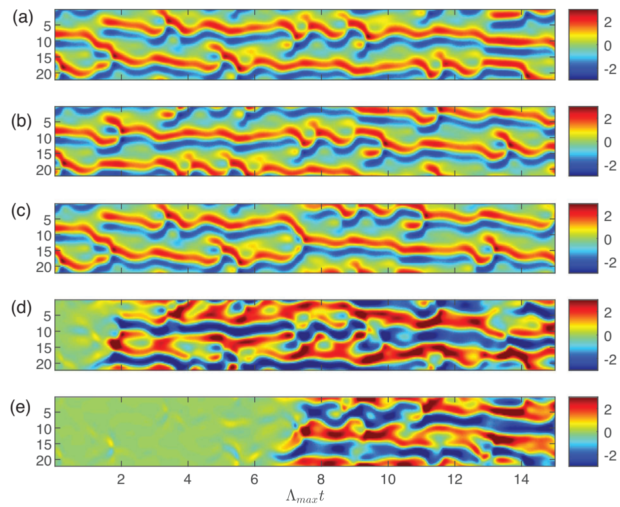

FIGURE 3 The proposed HENG-RC can learn and predict the dynamical characteristics of KS-equation in spatiotemporal domain. (a) The spatiotemporal evolution of the KS-equation; (b) The spatiotemporal evolution of the traditional RC after trained by KS; (c) The spatiotemporal evolution of the proposed HENG-RC after trained by KS; (d) Error dynamics of time series between the original system and the RC; (e) Error dynamics of time series between the original system and the proposed HENG-RC. $\Delta_{max}t$ is the largest Lyapunov time derived by multiplying maximum Lyapunov exponent and time

proposed HENG-RC uses less non-linear states for constructing the feature vector. The number of terms involved decide, to some extent, the efficiency of an algorithm. The high efficiency of the proposed HENG-RC will be more obviously in dealing with VLSCS.

3.2 | VLSCS: Kuramoto-Sivashinsky equation

The standard Kuramoto-Sivashinsky (KS) equation is taken as the VLSCS example. Here, we study the prediction performance based on the proposed HENG-RC. The KS equation is expressed by [30]:

$$y_t = -yy_x - y_{xx} - y_{xxxx}, \tag{11}$$

where the $y(x, t)$ is a scalar field. The scalar field is periodic in the interval of $[0, L]$. L can be seen as the scalar parameter in spatial dimension. The Equation (11) can be solved numerically to generate a data set $H(t)$. The $H(t)$ is derived with a time step of 0.25 on a grid of Q equidistant points, and thus the $H(t)$ can be considered as a Q-dimensional input sequence. The proposed HENG-RC is then proven to be able to predict the KS-equation. As shown in Figure 3c, with 40 largest Lyapunov training time, in prediction phase the proposed HENG-RC can output same results with the KS-equation for a certain time. Likewise, we also conduct the comparisons with the traditional RC. Based on the same training data set, the predicated spatiotemporal evolution of KS equation based on RC is given in Figure 3b. To be clearer, we calculate the error dynamics regarding to the predicated results and actual data generated by KS. The results using, RC and proposed HENG-RC, are presented in Figure 3d,e, respectively. It is shown that the accurate prediction length based on the proposed HENG-RC outperforms the traditional RC.

TABLE 1 The comparison of needed resources that decide the computational efficiency of RC using the case of VLSCS with $L = 22, Q = 64$

Model	States	Effective W_{out} [a]	Training length
RC[31]	3968	253,952	50,000
NG-RC	8385	536,640	/ [b]
HENG-RC	769	28,416	10,000

[a] The number of non-zero terms in W_{out}.

[b] The data of using NG-RC in [20] is unknown since the NG-RC was reported for studying low-dimensional chaotic system only. However, if the NG-RC is employed for this case, the states and effective weights numbers can be calculated, which are much larger than the proposed.

In addition, we, in Table 1, conduct the comparisons between RC, NG-RC and the proposed HENG-RCin terms of states involved for feature construction, training data length and number of effective weights. The comparison is based on the same task for predicting VLSCS with $L = 22$ and $Q = 64$. It can be seen that the proposed model needs the least states and effective weight numbers. We can use only 769 states, 28416 weights and 10,000 training points to accomplish the task that consumes RC 3968 states (neurons), 25,3952 weights and 50,000 training points. The efficiency is therefore much lowered. Since the original NG-RC is limited for studying low-dimensional systems, the comparison between the HENG-RC and NG-RC can only be reflected from the needed states and weights. Specifically, the original NG-RC involves a huge numbers of weights and states, i.e. 536,576 and 8385, several orders larger than the proposed HENG-RC.

To deeply understand why the proposed method works outstandingly in dealing with VLSCS, we analyse the values of weight (W_{out}) after being trained by a data set generated by the KS with setting $L = 22$ and $Q = 64$. The results are given in Figure 4. In Figure 4a, the weight values in W_{out}, under the absolute and Log operation, are derived based on the regular training. It can be seen that in Figure 4a the weights are to some extent localised, which means that the principle of local states correlation is reasonably applied for extracting the feature of input signal, and it is not necessary for using NVAR for constructing the feature vector during which many redundant states generate. In Figure 4b, we further present the result with attention mechanism considered. There is an obvious bright region appeared which proves that the attention can concentrate the key states for extracting the feature and thereby enhance the prediction performance as well as increase the efficiency.

4 | DYNAMICAL ANALYSIS

This section aims to investigate if the proposed HENG-RC can be seen as a data-driven dynamical model. First, the density distribution is investigated. Assuming that the HENG-RC is trained by the training data set generated by Lorenz system with length of 10^4, the trained HENG-RC can output similar

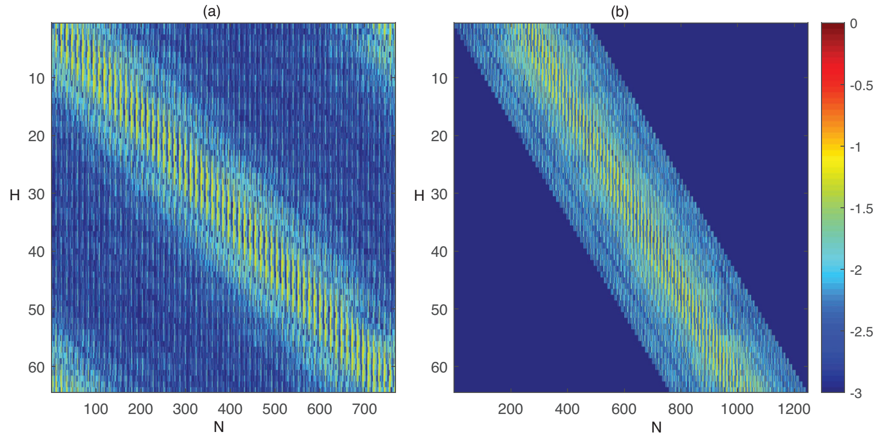

FIGURE 4 The values of weight matrix W_{out} of the proposed HENG-RC without the attention mechanism is shown in (a). Each point (n, i) represents the connection strength between nth state in feature vector and the i-dimension output. Note that the values are taken under the absolute and the logarithm operation. The values of weight matrix W_{out} of the proposed HENG-RC with the attention mechanism is shown in (b)

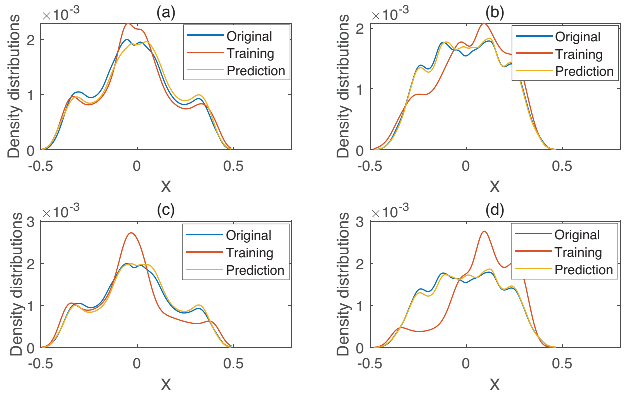

FIGURE 5 Density distribution of x-dimension of original Lorenz system and the output of proposed HENG-RC: (a) Training HENG-RC with data length 10^4 generated by Lorenz system ($\gamma = 28$); (b) Training HENG-RC with data length 10^4 generated by Lorenz system ($\gamma = 56$); (c) Training HENG-RC with data length 2×10^3 generated by Lorenz system ($\gamma = 28$); (d) Training HENG-RC with data length 2×10^3 generated by Lorenz system ($\gamma = 56$). The length of original system data and prediction data is 6×10^5 as close as possible to the extreme distribution of the data

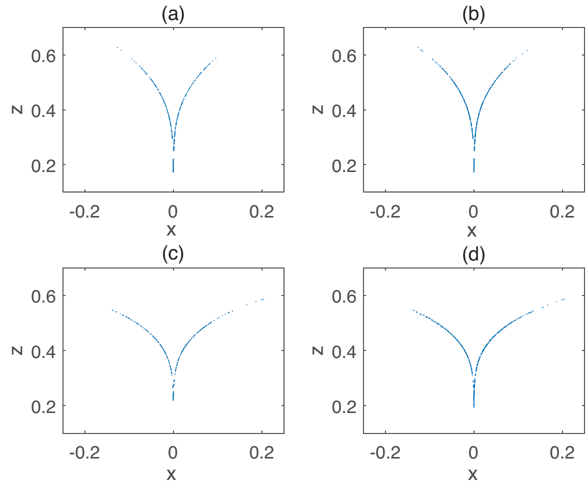

FIGURE 6 Poincaré section ($y = 0$) of the original Lorenz system and the output of the proposed HENG-RC: the point sets of (x, z) along a long trajectory of the actual Lorenz system (a,c), as well as along the output trajectory of the proposed HENG-RC (b,d), are plotted when $|y| < p$, where $p = 10^{-4}$. In (a,b) the parameter $\gamma = 28$ while (c,d) the $\gamma = 56$. The data length is 6×10^5

density distribution with the actual system in x-dimension, as shown in Figure 5a,b where the system parameter γ is taken differently. Moreover, we reduce the length of training data as 10^3. In such a case, the training data set cannot actually reflect the data distribution of the original system. Surprisingly, the trained HENG-RC can still output similar density distribution with the original, which proves that the proposed HENG-RC can learn the Lorenz system well. The results are present in Figure 5c,d.

We also plot the Poincaré section ($y = 0$) of the actual Lorenz system with different system parameter γ and the proposed HENG-RC after trained by a data set with length of 6×10^5. The results are presented in Figure 6. It is seen that the proposed HENG-RC can output similar Poincaré section as shown in Figure 5b,d, with the original system as shown in Figure 5a,c. We further calculate the maximum Lyapunov exponent, a positive value which indicates chaos, based on the observation of output data of the proposed HENG-RC after being trained. The detailed method for calculating the maximum Lyapunov exponent by observing a small data set can be found from [32].

The calculation of maximum Lyapunov exponent is then conducted and the result is shown in Figure 7, where the slope of the straight line is the maximum Lyapunov exponent. The maximum Lyapunov exponent of the original Lorenz chaotic system and the NG-RC are about 1.05 and 0.95, respectively. This can prove the unpredictability of the output of the trained NG-RC, and hence the trained NG-RC can be seen as an actual chaotic system.

5 | SECURE COMMUNICATION AND HARDWARE EXPERIMENT

The proposed HENG-RC can be seen as a data-driven dynamical model working in the chaotic state. In this section, we propose a secure communication scheme as shown in Figure 8. The transmitter and receiver are all equipped with a HENG-RC, where the HENC-RC behaves like an actual dynamical chaotic

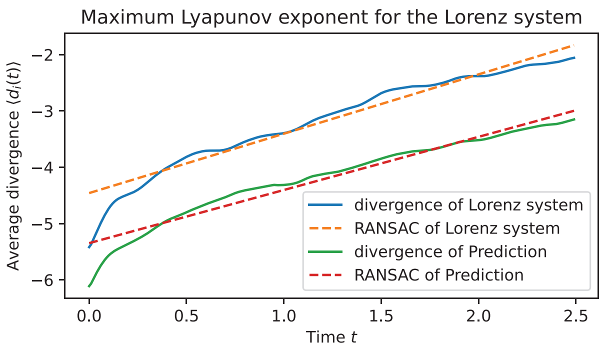

FIGURE 7 Maximum Lyapunov exponent calculation based on the observation of time series data. The blue (solid) and green (solid) line represents the original Lorenz system and the proposed HENG-RC after being trained, respectively, and the maximum Lyapunov exponent is extracted by calculating the slope of the two solid lines

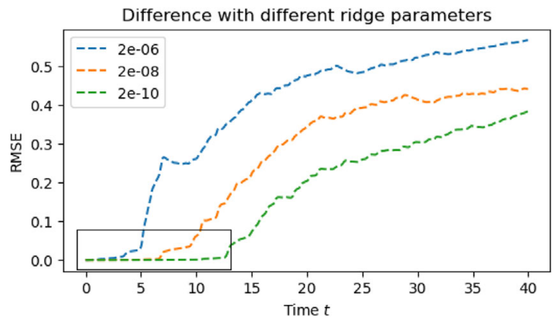

FIGURE 9 The synchronisation window modulation by setting different ridge parameters in the training process of two proposed HENG-RCs. The different time length of synchronisation, indicated by the black box, are calculated by setting ridge parameters: $\lambda_1 = \lambda_0 + 2 \times 10^{-6}, +2 \times 10^{-8}, +2 \times 10^{-10}$

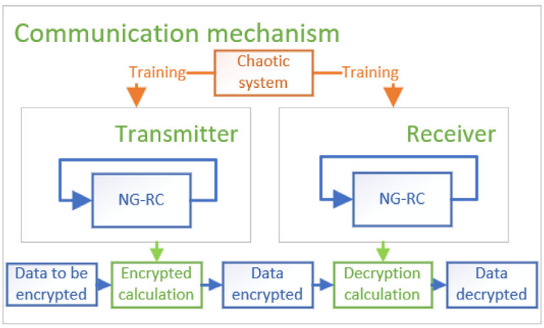

FIGURE 8 The secure communication scheme. The transmitter and receiver are both equipped with NG-RC and trained using a common chaotic system, indicated by the yellow block. The two NG-RCs are different in terms of parameters settings. The intruder has to know both the training signals and parameters settings for stealing the encrypted information

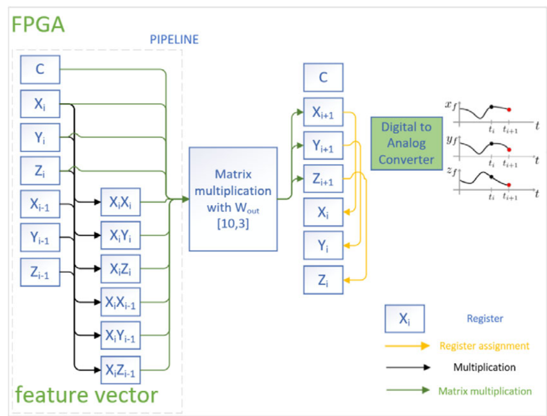

FIGURE 10 The FPGA design for the proposed HENG-RC. Operations of multiplication and matrix multiplication are indicated by black and green lines. X_i denotes register. The yellow lines with arrowhead show the process of register assignment

system. After trained by a common chaotic sequence generated by any chaotic systems, the two NG-RCs can achieve chaos synchronisation, and by utilising the chaos synchronisation the signal masked by chaotic signal can be decoded. The security of the scheme can be attributed to that the chaos synchronisation of HENG-RC provides a "hardware key" that the attacker who aims to steal the secret message has to know simultaneously the common training signal and all parameter settings related to the HENG-RC. In addition, with different ridge parameters in training phase, the synchronisation time is controllable to some extent, which can be used for enhancing the security of the scheme. We conduct the simulation that the two HENG-RCs are trained using parameters with a tiny differences. Specifically, the first one is trained with ridge parameter $\lambda_0 = 2 \times 10^{-6}$, and the second is trained with ridge parameter with tiny differences, i.e. $\lambda_1 = \lambda_0 + 2 \times 10^{-6}, +2 \times 10^{-8}, +2 \times 10^{-10}$. The calculated RMSE of the three cases are given in Figure 9. It is shown that with different ridge parameters the synchronisation time between two HENG-RC, indicated by the dashed box, can be modulated in a certain range. Therefore, in practical secure communication, one can set RHE appropriate time window depending on specific tasks.

For digital circuit implementation, the proposed secure communication can avoid the problems such as disturbance brought by analog devices. It does not involve random numbers and large matrix multiplication as in the traditional RC models. Here, we use the field programmable gate array (FPGA) to implement the proposed scheme. The specific digital circuit design is given in Figure 10. It is mainly composed of two modules: feature vector and output weight matrix. The design circuit can run in 30 clock cycles with double-float precision by using pipeline optimisation.

Experimentally, the Xilinx ZYNQ 7020 Soc is used to realise the HENG-RC. By taking the Lorenz system as the source of training signal, the synchronisation result is displayed on oscilloscope via a digital to analog converter (DAC) unit. The experimental setup and actual results are present in Figure 11. It is seen that the digital design can well be used for implementing the scheme, with stable chaos synchronisation achieved between the two hardware realised HENG-RCs. Figure 12 is given for providing a clear evidence of the achieved chaos synchronisation.

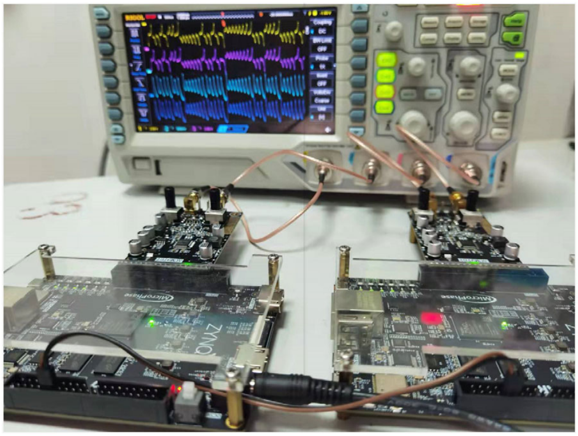

FIGURE 11 Hardware experiment based on the two proposed HENG-RC and the synchronising signals is shown on the oscilloscope

FIGURE 12 Clear synchronisation results on oscilloscope during the experiment. The yellow line represents the *y*-dimension signal of first proposed HENG-RC; The pink line represents the *y*-dimension signal of the second proposed HENG-RC; The blue line represents the *z*-dimension signal of the first proposed HENG-RC and the cyan line represents the *z*-dimension signal of the second proposed HENG-RC

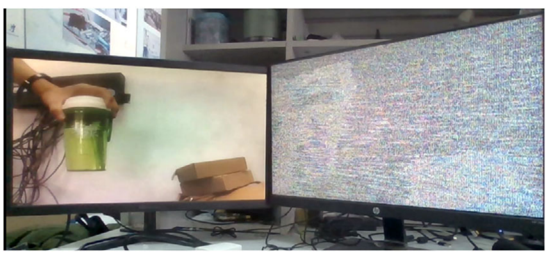

FIGURE 13 The NG-RC in transmitter after trained can encrypt the video data, and the encrypted data are displayed on the right screen

Moreover, based on the chaos synchronisation achieved between two HENG-RC in transmitter and receiver, respectively, the practical video communication is tested, where the transmitter and receiver communicate via Ethernet. Except for the limited training set to synchronise the two ends, there is no additional overhead for transmitting data. As shown in Figure 13, the NG-RC after trained in transmitter can be used

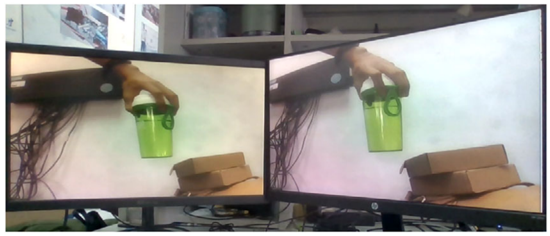

FIGURE 14 The NG-RC in receiver after trained by the common signal can decrypt the sending video data. From the result displayed on the two screens one can conclude that our secret communication scheme can work successfully

for encrypting the video information. And in Figure 14, the NG-RC after trained can decrypt the received information.

6 | CONCLUSION

A novel HENG-RC paradigm which incorporates the principles of local states correlation and attention mechanism has been proposed. The HENG-RC demonstrates outstanding performance for chaotic time series prediction regarding to both low-dimensional chaotic system and VLSCS. Particularly for VLSCS, the HENG-RC shows a high efficiency. The HENG-RC after being trained is revealed for behaving like an actual data-driven chaotic system. Based on chaos synchronisation between the two HENG-RCs, a novel secure communication scheme has been designed. The security of which is enhanced attributing to the fact that the intruder has to know the training signal and all the details of parameters setting in HENG-RC simultaneously. By using FPGA, the digital chaos synchronisation of the HENG-RC is experimentally realised, which proves that the scheme can work in practical. Our work advances the cross-over study between machine learning approaches and nonlinear dynamics, as well as sheds light on realising secure communication based on data-driven models.

AUTHOR CONTRIBUTIONS

Leisheng Jin: Conceptualization, data curation, investigation, methodology, resources, software, validation, writing - original draft, writing - review and editing. Zhuo Liu: Software, validation, visualization, writing - original draft. Ai Guan: Data curation, software, validation. Zhen Wang: Data curation, software, validation. Rui Xue: Software, validation. Lijie Li: Conceptualization, funding acquisition, investigation, methodology, project administration, supervision, writing - review and editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data will be made available on reasonable request.

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