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A New Wavelet-based Research and Implementation for Open Packaging Conventions

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Abstract: This study presents a new wavelet-based noise reduction scheme based on the lifting scheme and genetic algorithms, which is a novel approach by using a Genetic Algorithm and lifting wavelet framework for threshold selection. There are two folders in this approach. Firstly, it adapts itself to various types of noises without any prior knowledge of noise; secondly, it suppresses noises while preserving the dynamics of the signals. The experimental evaluation is conducted to compare the performances of the new method with existing approaches and the applications for signal denoising are investigated in this study.

Key words: Chaotic signal, denoising, wavelet transform, lifting scheme, genetic algorithm, wavelet threshold

INTRODUCTION

The chaotic signal is often contaminated by noise. The presence of noise often greatly influences the analysis of the data and causes the limitation of the performance of many techniques. Therefore, it is desirable to reduce the noise level without distorting the dynamics of the signal.

A lot of works were carried out by noise reduction methods. Some of them either using linear or nonlinear filtering. However, linear filtering does not work very well for overlapping bandwidths of chaotic signals (Wei and Shu, 2007). On the other hand, nonlinear filtering, such as the median filter, often distorts the dynamics of signal.

Wavelet Transforms (WT) have received considerable attention in recent years, because it provides a trade-off between time-frequency resolutions and allows flexible exploiting of a signal at different resolution levels. Therefore, noise reduction methods that based on the classical WT are superior to linear and nonlinear filtering. However, most of the wavelet shareholding methods (Han and Liu, 2009; Liu and Liao, 2011) are often suffer from some drawbacks, which is refer to the selected threshold may not match the specific distribution of signal and noise components in different scales, especially for the noisy chaotic signals, where both the Signal-to-Noise Ratio (SNR) and the dynamics of a signal are equally important. In fact, chaotic data often suffer from different types of noises, such as white noise and colored noise (Sun *et al*., 2007). An ideal method is denoising by learning the noise types from the signal themselves without a priori knowledge intelligently.

Genetic Algorithms (GA), which is one of the stochastic methods of optimization, has been commonly used for the optimal design. The main advantages of the Genetic Algorithms (GAs) are not using the derivatives and functions with discrete and non-derivable variables (Marcelin, 2001). This study presents an innovative approach to select an optimal threshold for each subband at different scales, which was using Genetic Algorithm (GA) to achieve both noise reduction and feature preservation.

Because there are many challenges will be encountered during its construction and led to lifting wavelet transform or lifting scheme (Sweldens, 1995), an entire spatial domain method where Fourier transforms in is not required. The lifting scheme provides a great deal of flexibilities and can be designed according to the properties of the given signal. In addition, the process of the construction of the lifting is efficient. It needs less computational time.

Based on lifting wavelet transform, a new wavelet-based chaotic signal denoising that using lifting scheme and genetic algorithms is proposed in this study.

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LIFTING SCHEME

The lifting scheme consists of three basic steps:

Split: The original data set x[n] is spitted into indexed points $x_e[n] = x[2n]$ and odd indexed points $x_o[n] = x[2n+1]$.

Predict: As the differences in prediction of $x_o[n]$ from $x_e[n]$, detailed wavelet coefficients d[n] is obtained by using the prediction operator P:

$$d[n] = x_o[n] - P(x_e[n]) \tag{1}$$

Update: Generating approximation coefficients a[n] by combining the indexed points $x_e[n]$ and detailed coefficients d[n] by applying update operator U to the detailed coefficients d[n]:

$$a[n] = x_e[n] + U(d[n]) \tag{2}$$

The general single-level forward lifting scheme is given in Fig. 1. The lifting steps can be easily inverted. The inverse lifting scheme is given in Fig. 2 and can be decomposed into three steps:

Undo update: By using Eq. 2, we have:

$$x_e[n] = a[n] - U(d[n]) \tag{3}$$

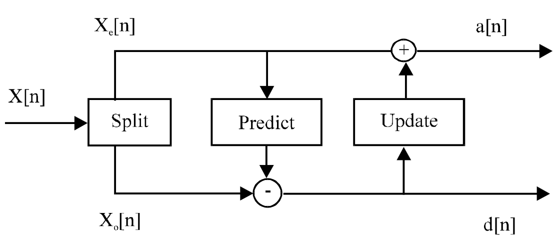

Fig. 1: Forward lifting scheme

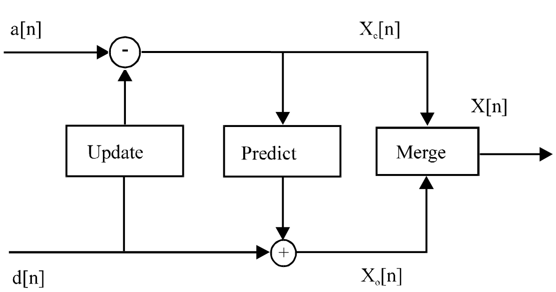

Fig. 2: Inverse lifting scheme

Undo predict: From Eq. 1, we get:

$$x_o[n] = d[n] + P(x_e[n]) \tag{4}$$

Merge: The estimation of the original signal can be obtained by combining Eq. 3 and 4.

GENETIC ALGORITHM

GA is a global optimization method which is based on the principles of natural selection and evolutionary theory (Holland, 1975). The algorithm is provided with a set of possible chromosomes and termed a population. Solutions from one population are taken and used to form new population. This is motivated by a hope that the new population will perform better than their predecessors. Solutions chosen to form new offsprings are selected based on their fitness-the more suitable they are, the better their chances will be reproduced. This process of selection is repeated till some predetermined condition is satisfied (Chakraborty *et al.*, 2003). The flowchart for solving the discrete optimization problem by using GA is illustrated in Fig. 3.

CHAOTIC SIGNALS DENOISING BY USING LIFTING WAVELET SCHEME AND GA

One important feature of the wavelet that based on denoising is that the processing of coefficients independently from each other is suggested by the decorrelation property of wavelet. The sparseness property paves a way to use thresholds to remove the

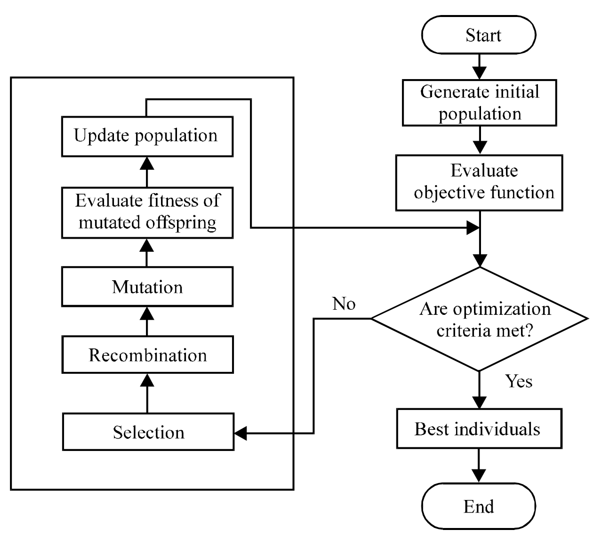

Fig. 3: Structure of a simple genetic algorithm

wavelet coefficients that are 'small' to the noise level, respectively. This process is called wavelet thresholding, because the coefficients are shrunk toward zero.

The soft thresholding function of the wavelet coefficient matrix x with threshold T can be expressed as follows:

$$\lambda_{soft} = x, T \text{ if } x = T = 0 \text{ if } |x|<T = x+T \text{ if } x = -T \quad (5)$$

Similarly, the hard thresholding function is expressed as follows:

$$\lambda_{hard} = x \text{ if } x = T \ = 0 \text{ otherwise} \quad (6)$$

In the hard thresholding scheme, the wavelet coefficients which are greater than the threshold are retained while the coefficients that are less than the threshold are set to zero. Comparing with both hard and soft shrinking schemes, the hard thresholding are exhibiting in some discontinuities and even be unstable or more sensitive to small changes in the data. On the other hand, the soft thresholding scheme avoids discontinuities and is more stable than the hard thresholding. The idea of thresholding is simple and effective. However, the selection of optimal threshold value is a challenging task, because it directly affects the result of denoising. Choosing a very high threshold will almost shrink all the coefficients to zero and may result in excessive smoothing of the dynamics features. On the other hand, a small value of the threshold will keep the dynamics and details retain, but may fail to suppress the noise as well. To overcome this limitation, wavelet thresholding has been addressed by using Gradient Decent algorithm. The basic idea of Gradient Decent algorithm is adding the sigmoid threshold filtering unit to the details. The parameters of Sigmoid threshold filtering are adjusted according to the Gradient Decent algorithm until the Root Mean Square Error (RMSE) achieves the minimum value and the adaptive choice of detailed coefficients is obtained. The RMSE is defined as the error criteria of noise reduction in this method. Unfortunately, the dependency of the method to a specific type of noise and careful hand-tuning of the parameters of Sigmoid threshold filtering are decreasing its flexibility to process real world chaotic signals. As a consequence, intelligent threshold optimization is a key problem for chaotic wavelet denoising.

Optimal solution for threshold selection based on Ga: GA is one of the most widely used artificial intelligent techniques for optimization. GAs have been proven to be very efficient and stable method in searching for global optimum solutions (Shao and Barner, 2006). The present work has made an attempt to introduce GA for threshold optimization in wavelet denoising framework. The GA procedure that adopted for the present study is briefly described below.

Chromosome encoding: Real-coded GA is used in our study. The chromosome representation used to encode the threshold values needs to be optimized. Each chromosome is an n-dimensional real value vector. Each gene represents a threshold assignment which is associated with a real value.

Fitness function and selection operation: In this step, chromosomes from the parent population are selected in pairs with a probability proportional to their fitness to replicate and form offspring chromosomes. Roulette wheel selection is used in our study. The often-desired feature of chaotic signals applications is not only high SNR, but also good dynamics characteristic. Hence, the objective of the present study is to maximize the SNR and minimize the Liu's error factor at the same time (Han *et al*., 2007).

The fitness function is written as:

$$\text{Fitness function} = \text{M ax}(\text{SNR}(\hat{f}) - (\text{F}(\hat{f})) \quad (7)$$

Where:

$$\text{SNR}(\hat{f}) = \frac{\text{ROI}_{signal}(\hat{f})}{\text{ROI}_{noise}(\hat{f})},\ \text{F}(\hat{f}) = \frac{1}{1000(\text{NM})}\sqrt{R}\sum_{i=1}^{R}\frac{e_i^2}{\sqrt{A_i}}$$

Crossover operator: If a probability test is passed, the parent chromosomes are combined and mutated to form the offspring chromosomes after the selection. Because the encoding is a real-coded GA, we use the crossover operators as follows. Let us assume that $S_1 = (v_1^{(1)}, v_2^{(1)}, \ldots, v_n^{(1)})$ and $S_2 = (v_1^{(2)}, v_2^{(2)}, \ldots, v_n^{(2)})$ are the two chromosomes that are selected for the application of the crossover operator. The two offsprings, $S_z = (z_1, z_2, \ldots, z_n)$ and $S_w = (w_1, w_2, \ldots, w_n)$ are generated, where:

$$S_z = (v_1^{(1)}, v_2^{(1)}, \ldots, v_k^{(1)}, a_{k+1}v_k^{(1)}+(1-a_{k+1})\, v_{k+1}^{(2)}, \ldots, a_n\, v_n^{(1)}+(1-a_n)\, v_n^{(2)})$$

$$S_w = (v_1^{(2)}, v_2^{(2)}, \ldots, v_k^{(2)}, a_{k+1}v_k^{(2)}+(1-a_{k+1})v_{k+1}^{(1)}, \ldots, a_n\, v_n^{(2)}+(1-a_n)\, v_n^{(1)})$$

where $a_1, a_2, \ldots, a_n (0, 1)$ are constant parameters and $a_1, a_2, \ldots, a_n$ are equal to 0.2.

Mutation operator: After the crossover operation, chromosomes are subjected to a mutation operation. The non-uniformity mutation operator is used to take advantage of the real-coded representation of the solution space. Let us assume $S = (v_1, v_2, \ldots, v_n)$ is a chromosome and the element v_k is selected for mutation (domain of v_k is $[a_k, b_k]$), the result is a vector $S' = (v_1, \ldots v_{k-1}, v_k, \ldots, v_n)$. Where v_k' is given by:

$$v_k' = \begin{cases} v_k + \Delta(t, b_k - v_k) & \text{if} \quad rnd() = 1 \\ v_k - \Delta(t, v_k - a_k) & \text{if} \quad rnd() = 0 \end{cases} \tag{8}$$

where rnd() is a pseudorandom number function and t is the number of generations. The function Δ(t, y) returns a value within the range [0, y] such that the probability of Δ(t, y) being close to 0 as t increases. We have used the following function:

$$\Delta(t,y) = y\left(1 - r^{(1-\frac{t}{T})^{\lambda}}\right) \tag{9}$$

Where r is a random number from the interval [0,1], T is the maximal generation number and λ is a system parameter that determining the degree of non-uniformity (λ [2, 5]).

Stopping condition: Three criteria are set as the stopping condition for the GA adopted in present study: (1) The total number of iterations reaches a predefined number of iterations (2) The fittest chromosome of each generation has not changed much, that is, the difference is less than 10^{-3} over a predefined number.

Procedure of chaotic signals denoising by using lifting wavelet scheme and GA: The main steps of Lifting-GA that based on denoising algorithm for optimal selection of wavelet thresholds for each subband proposed in this study are summarized as follows:

- **Step 1:** Initializing crossover and mutation probability and generating random population
- **Step 2:** Calculating the fitness value by using Eq. 7 and the selection probability
- **Step 3:** Selecting parents and applying crossover and create offspring
- **Step 4:** Mutating offspring and replacing the old population by the new one
- **Step 5:** If the termination condition is met, then stop; otherwise, go back to Step 2
- **Step 6:** Applying lifting WT on chaotic signals to get subbands
- **Step 7:** Threshold subbands by using GA optimized threshold values
- **Step 8:** Applying Inverse lifting WT to reconstruct denoised chaotic signals

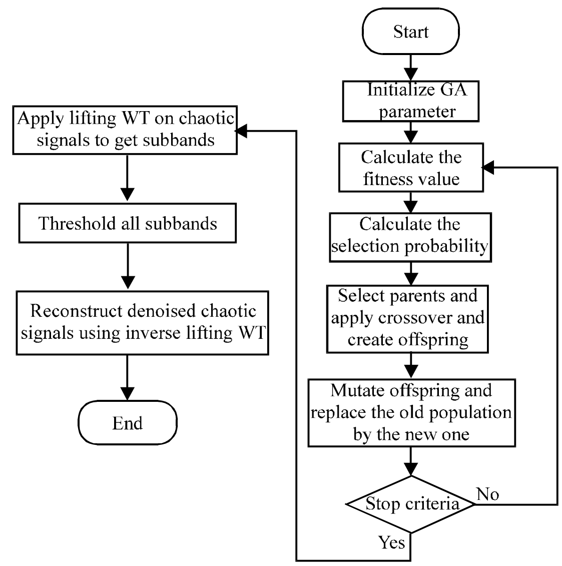

Fig. 4: Flow chart of lifting-GA based denoising algorithm

The flow chart of the Lifting-GA that based on denoising algorithm is shown in Fig. 4.

RESULTS AND DISCUSSION

The proposed method was first applied to chaotic signals which are generated by Rossler system and then applied to chaotic signals that generated by Lorenz system to check the effectiveness of the proposed noise reduction algorithm. In order to evaluate the performance of the new approach, soft-threshold wavelet method (Han *et al*., 2007) and adaptive chaotic noise reduction method (Liu and Liao, 2011) are used to denoise the same chaotic signals. The parameters of real-coded GA: The crossover ratio is 0.3; the mutation ratio is 0.06; the population size is 50; the maximal generation number T equals to 300 and the algorithm repeats 20 times.

In all our experiments listed below, we use the Daubechies order 4 wavelet. Daubechies 4 (DB4) wavelet is found to perform better in preserving dynamics feature. The compact spatial support of DB4 wavelet with four vanishing moments can provide better frequency localization and approximation, which will lead to good performance (Wei *et al*., 2010a, b).

Application to chaotic signal that generated by rossler gaussian colored noise modeling: To investigate the efficiency of the Lifting-GA that based on the methods for Gaussian colored noise removal, noisy chaotic signal are simulated by corrupting the chaotic signal which generated by Rossler with Gaussian colored noise. The

Table 1: Pseudo steps for Gaussian colored noise modeling

Step 1:	Initialize step size $\Delta t = 10^{-3}$ and correlation time $\lambda^{-1} = 2.5\times10^{-3}$
Step 2:	Generate four random numbers m, n, a, b using built-in function rand(), which are uniformly distributed on [0, 1]
Step 3:	Simulate gaussian colored noise g_c as defined below, $g_c = eE+h$, where $e = \sqrt{-2\lambda \ln(m)}\cos(2\pi n)$, $E = \exp(-\lambda\Delta t)$, $h = \sqrt{-2\lambda(1-E^2)\ln(a)}\cos(2\pi b)$
Step 4:	Reference signal is corrupted by noise $f'(x) = f(x)+g_c$ in which $f'(x)$ is noisy signal, f(x) is the clean signal and g_{gr} is gaussian colored noise

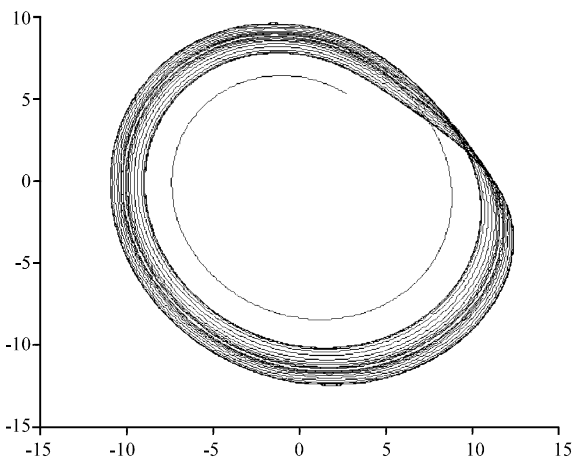

Fig. 5: View of the classical rossler attractor

Gaussian colored noises are generated according to the pseudo steps, which showed in Table 1. The view of the classical Rossler attractor is shown in Fig 5. The chaotic signals which the SNR is set to 14.7381 dB are shown in Fig. 6a.

Comparison of performance: In order to achive the purpose of comparion, the denoising results of the lifting-GA that based on the approach and the soft-threshold wavelet and adaptive chaotic noise reduction methods to Gaussian colored noise added Rossler system are presented in Fig. 6. Columns (b) and (c) show the performance of the soft-threshold wavelet and adaptive chaotic noise reduction methods respectively and column, (d) presents the results of the lifting-GA method. Throughing our visual inspection of the results, it can be observed that the soft-threshold wavelet distorts the dynamics of chaotic attractor of Rossler system. On the other hand, the adaptive chaotic noise reduction method are more effective in suppressing noise and preserving the dynamics than the soft-threshold method. However, noise corruption in some regions are still be observed. We can see that the lifting-GA-based method suppresses noises and be more effective in maintaining the dynamic of signals than the other two methods, which are also showing good visualization of adjacent regions of similar intensity

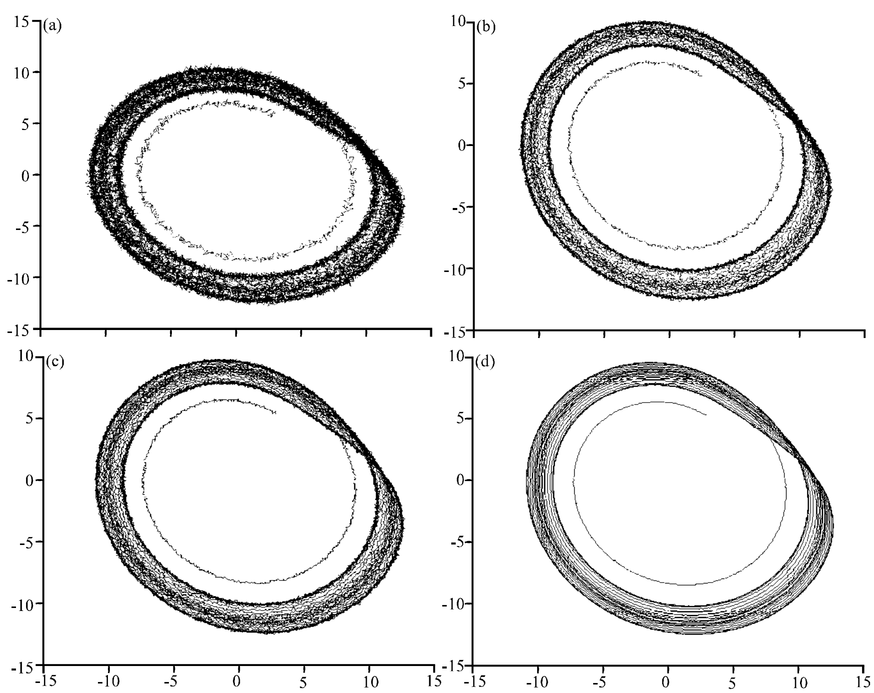

Fig. 6(a-d): View of rossler signal, (a) Rossler signal with SNR = 14.7381 dB, (b) Denoised data with the soft-threshold wavelet method, (c) Denoised data with the adative chaotic noise reduction method and (d) Deoised data with the proposed method in this study

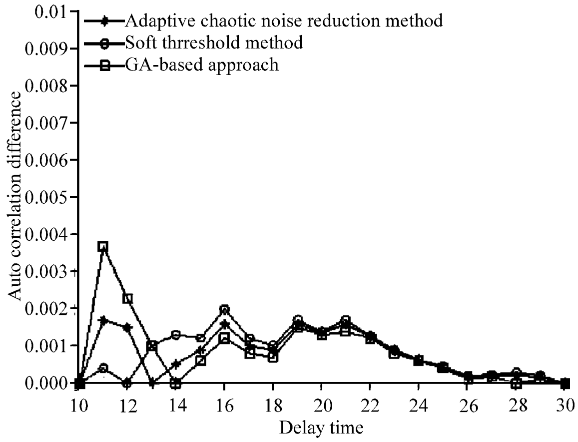

Fig. 7: Autocorrelation difference map of rossler signal after noise reduction

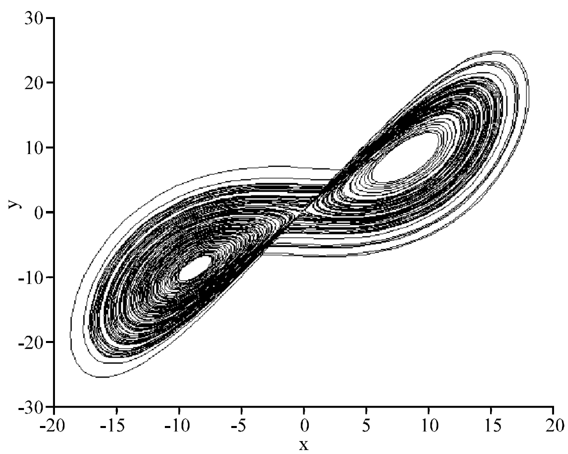

Fig. 8: View of the classical Lorenz attractor

Table 2: Comparison of the performance of three noise reduction methods on rossler signals

Methods	SNR	RMSE
None	14.7381	0.5502
Soft-threshold wavelet method	20.9845	0.4278
Adaptive chaotic noise reduction method	22.9713	0.3771
Lifting-GA based method	26.1291	0.2378

Table 3: Pseudo steps for gaussian white noise modeling

Step 1: Initializing step size $\Delta t = 10^{-3}$

Step 2: Generating two random numbers a, b by using built-in function rand(), which are uniformly distributed on [0, 1]

Step 3: Simulating gaussian white noise g_w as defined below,

$$g_w = \mu + \sigma\sqrt{-2\ln(a)}\cos(2\pi b)$$

where $g_w \sim N(\mu, \sigma^2)$, μ is the mean and σ^2 is the variance

Step 4: The reference signal is corrupted by noise $f'(x) = f(x)+g_w$, in which $f'(x)$ is noisy signal, f(x) is the clean signal and g_w is Gaussian white noise

characteristics with well-delineated boundaries and improving the whole performance of the system (Wei and Ma, 2012; Wei and Qi, 2011).

For the purpose of thorough checking the effectiveness of the proposed method for chaotic signals with Gaussian colored noise modeling, we have analyzed the difference of autocorrelation function from the domain of time. When the delay time is 10, 11, 12, 13, ...,30 sec, the autocorrelation difference map of the Rossler signal after noise reduction is shown in Fig. 7. From Fig. 7, we can see that after the applying of lifting-GA-based method, the autocorrelation difference of Rossler signal is smaller than other methods in the same delay time. It fully illustrated that the signal generated by Rossler is more similar to the original signal; moreover, more noises are eliminated.

Table 2, the comparison of the performance of three noise reduction methods on Rossler signals.

From Table 2, we may have a clearly understanding of the improvement performance of the proposed method in this study. Compared with the soft-threshold wavelet method and adaptive chaotic noise reduction method, we can see that the lifting-GA-based method will further enhance the SNR of Rossler system and reduces the RMSE.

Through the above investigation, we can observe that the lifting-GA-based noise reduction method has better effectiveness in maintaining the dynamic of signals and the distortion with this presented method is much less than the other two methods. And we can also see that it enhances the whole performance of the scheme (Wei *et al*., 2010b).

Application to chaotic signal generated by Lorenz Gaussian white noise modeling: To investigate the efficiency of the proposed method for Gaussian white noise removal, noisy chaotic signal is simulated by corrupting the chaotic signal that generated by Lorenz with Gaussian white noise. The Gaussian white noises are generated according to the pseudo steps which given in Table 3, which using Box-Mueller algorithm from two random numbers and be uniformly distributed on the unit interval. The view of the classical Lorenz attractor is shown in Fig. 8 and the chaotic signals which the SNR is set to 15.0124 dB are shown in Fig. 9a.

Experimental evaluation: In order to check the effectiveness of the proposed noise reduction algorithm, we make use of the soft-threshold wavelet method, the adaptive chaotic noise reduction method and the lifting-GA-based approach for noise reduction of noisy Lorenz signal, respectively. The briefly view of Lorenz signal before and after noise reduction are shown as Fig. 9.

The comparison of the above three noise reduction methods on RMSE and SNRG are shown as Table 4. According to Table 4, the SNRG and RMSE curve can be

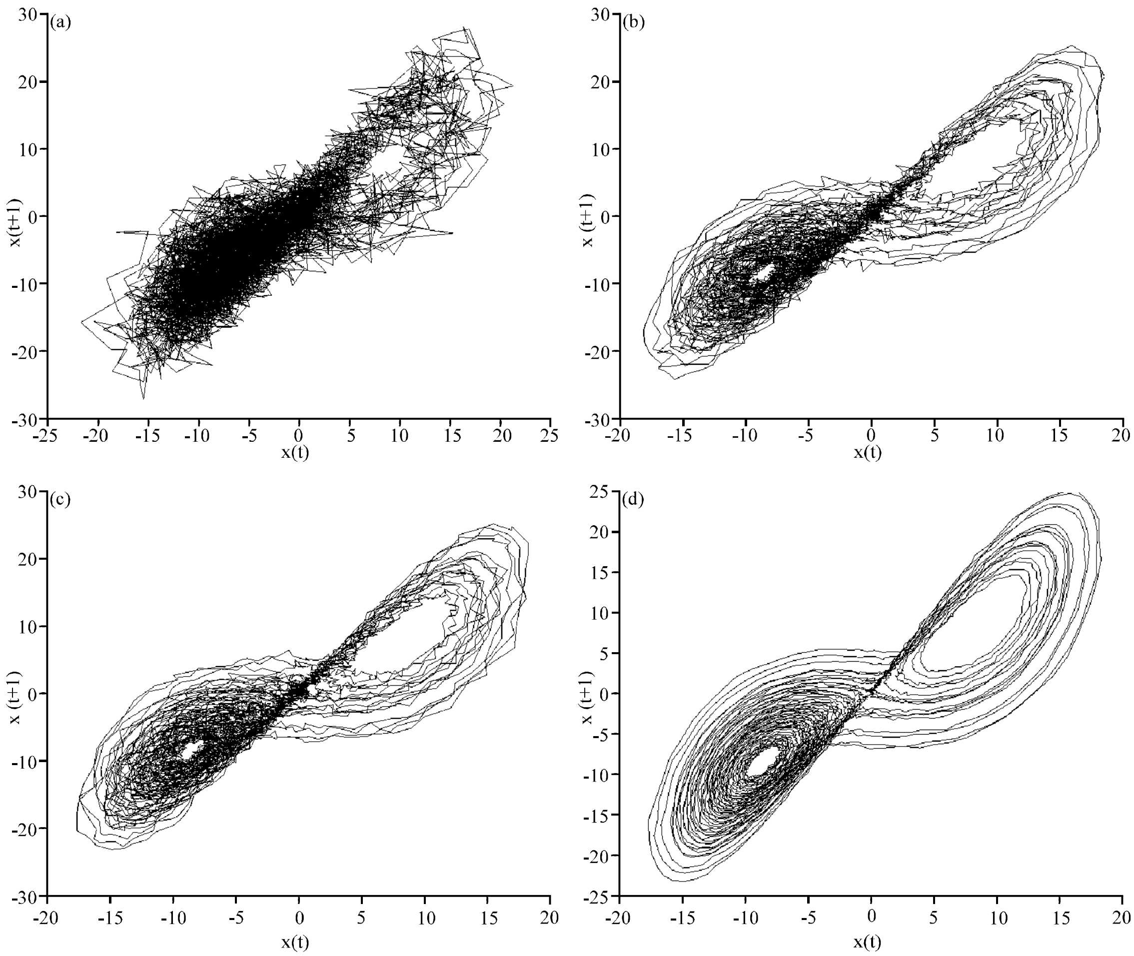

Fig. 9(a-d): View of Lorenz signal, (a) Lorenz signal with SNR = 15.0124 dB, (b) Denoised data with the soft-threshold wavelet method, (c) Denoised data with the adaptive chaotic noise reduction method and (d) Denoised data with the proposed method in this study

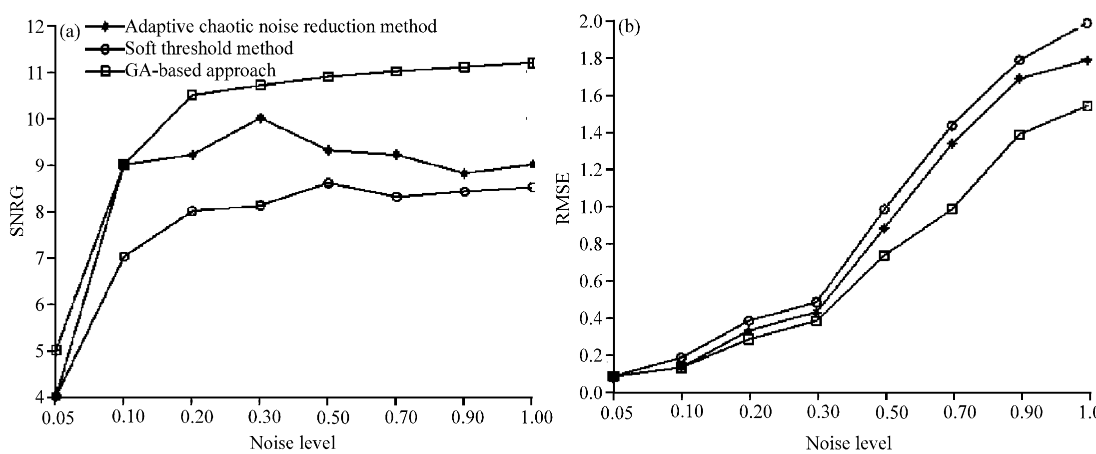

Fig. 10(a-b): SNRG and RMSE are curved with different noise levels, (a) SNRG curve and (b) RMSE curve

generated with different noise levels. The SNRG and RMSE curve are shown in Fig. 10 as the noise level is 5, 10, 20, 30, 50, 70, 90 and 100%, respectively.

From Table 4 and Fig. 10, we may have a clearly understanding of the improvement performance of the proposed method of this study. Compared with the

Table 4: Comparison of the performance of three noise reduction methods on Lorenz signals

Method	RMSE	SNRG
Soft-threshold wavelet method	0.5123	7.8745
Adaptive chaotic noise reduction method	0.3199	8.8923
Lifting-GA based method	0.2157	9.9873

soft-threshold wavelet method and adaptive chaotic noise reduction method, the lifting-GA-based method further enhances the SNRG of Lorenz system and reduces the RMSE (Wei and Jun, 2012).

CONCLUSION

A new lifting-GA-based denoising technique, which is applied to noisy chaotic signals, is introduced in this study. Its performance is evaluated by the using of different chaotic signals that generated by Lorenz system and Rossler system respectively and the comparison with other approaches that based on soft-threshold wavelet and sigmoid threshold dual-lifting wavelet. The results have revealed that the performances of this method are superior to the other two methods, which indicating its potential to reduce noise that existing not only in the present of Gaussian white noise but also in Gaussian colored noise. An interesting result of this study is that the insight into the trade-off between the SNR and the dynamics of signals. This technique provides a feasible way to suppress noise across the different sub-band of a signal without a priori knowledge of the noise.

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