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Research on Image Signal Identification Based on Adaptive Array Stochastic Resonance*

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Abstract Aiming at the problems of low accuracy of image signal identification and poor anti-noise signal interference ability under strong noise environment, a signal identification method of correlated noisy image based on adaptive array stochastic resonance (SR) is proposed in this paper. Firstly, the two-dimensional grayscale image is transformed to a one-dimensional binary pulse amplitude modulation (BPAM) signal with periodicity by the row or column scanning method, encoding and modulation. Then, the one-dimensional low signal-to-noise ratio BPAM signal can be applied to the saturating nonlinearity array SR module for image signal identification processing and part of the noise energy is converted into signal energy. Finally, the one-dimensional image signal processed by the nonlinearities is demodulated, decoded and reverse scanned to get the restored grayscale image. The simulation results show that the image signal identification method proposed in this paper is highly efficient and accurate for the identification of noisy image signals of different sizes, and the bit error rate (BER) is also significantly reduced.

Keywords Array stochastic resonance, bit error rate, image restoration, saturating nonlinearity; signal identification.

1 Introduction

In communication applications, almost all communication transmissions are signal interactions. But in fact, most of the collected signals contain noise signals or a mixture of multiple signals[1,2]. Therefore, signal identification not only played an important role, but also has been applied in many research fields. At present, methods for identifying or removing noise signals based on SR are gradually emerging. Stochastic resonance[3,4] can be described the nonlinear phenomenon that the response of the nonlinear system can be enhanced with the presence of

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internal or external noise when there is a certain match between the input signal and noise signal in the nonlinear system, the presence of noise signals can enhance the ability to identify weak signals and part of the noise energy is converted into useful signal energy. SR is used to process signal identification. Therefore, it has also a new method with practical application value[5].

Digital image signal processing has gradually been observed in an increasing variety of nonlinear processes and its application fields ranging from image restoration, pattern classification and recognition, and weak signals detection with SR in analytical chemistry, and so on[6−11]. The characteristics of the signal can be enhanced by the additive noise[12−16], breaking the rules that the signal can only be enhanced by eliminating noise, and has been widely used in the identification and estimation of weak signals, broadening the research ideas of signal identification[17−20]. Liu, et al.[21] proposed a segmentation based image denoising algorithm. The final denoising image is obtained by composing the denoised segments. Experimental results show that the algorithm outperforms state-of-the-art denoising algorithms in removing real signal dependent noise. Sun, et al.[22] developed a new recognition method for cracked hen egg with high accuracy and adoption. According to the change regulation of the local gray value of the crack area in the egg image, a sequenced wave signal extraction and identification algorithm was developed. The experimental results show that this method is more accurate in identifying egg image cracks. Chen, et al.[23] proposed a signal identification algorithm for signals composed of a sum of periodic signals. By using several internal models paralleled with a tuning function, in this algorithm signals composed of multiple harmonics with uncertain frequencies amplitudes and relative phases can be predicted or identified. The simulation result shows a good tracking of the original signal without disturbances. Although an effective effect can be obtained in signal identification and eliminate signal errors[24,25] in these methods, the traditional single-channel systems[26] for signal identification processing to improve the accuracy of signal identification is adopted, and the poor anti-interference ability and large identification error is obtained.

With the continuous research and development of signal identification, the multi-channel array theory has emerged and is used to deal with interfering signals in the process of signal identification[27]. The multiple channels is selected to test simultaneously to analyze several suitable test signals for identification in [28–30], in order to eliminate the interaction between multiple input signals. A new design method is proposed for the period length of uncorrelated pseudo-random signals. In addition, for a binary inputs system, there are special signal designs that utilize the property of reverse repeat pseudo random binary sequence signal special signal design. The pseudo random signal obtained by the simulation result processing is not only identifiable, but also has a short period. In [31] the HILR array is selected to record the waveform generated by the explosion, and the array technology is used to identify weak signals. The analysis results show that the signal-to-noise ratio after beam forming is significantly enhanced and the signal can be displayed clearly. The evaluation and identification of weak signals are significant for the detection of pseudo-random signals, the study of identification image signals and the application of binary-valued observation systems[32,33]. The identification and processing of weak signals have always received considerable attention. The existing signal identification processing method based on array SR reduces the accidental errors caused by a single nonlinear system by introducing multiple independent interference signals, thereby enhancing the SR signal identification effect and improving the reliability of the array system. However, these methods[34−36] lack the study on the bit error rate of signal identification, and the signal-to-noise ratio (SNR) needs to be improved, and its effect is not ideal.

Based on the signal identification, in this paper a saturating array model is proposed with image signal identification method which is used to restore and enhance the two-dimensional gray image interfered by the noise signal and to improve the bit error rate of the restored image signal identification. In this paper, by adopting a saturating array model, using parallel multiple saturating systems to do multi-channel processing of noisy image signals, and using parameter fine-tuning theory to process two-dimensional images, the image performance can be directly improved. Our proposed method can process grayscale images or high-level color images through dimensionality reduction and encoding. Therefore, the proposed method is expected to provide well improvement ability on the restoration of a noisy grayscale image at low PSNR. In order to make comparison experiment with the image signal recognition effect obtained by the method of this paper, mean filtering[37], Wiener filtering[38] and two-dimensional stochastic resonance method are selected[39,40]. The main works in this paper are presented as follows: 1) An array model based on saturating nonlinearities for signal identification is proposed. By adjusting the array size and the parameters of the saturating nonlinearity, the noisy signals can be processed well and accurate identified image signals can be obtained to achieve good image restoration effects. 2) Compared to the traditional filtering method and the two-dimensional stochastic resonance, the better restored image and the larger PSNR can be obtained by the array model and the smaller bit error rate can be got. 3) In the strong interference signal environment, a variety of noisy image signals of different sizes are identified, and the visual effect of the restored image is remarkable. The simulation results show that the large PSNR of the the restored image of the model and a low BER can be obtained. Therefore, the signal recognition rate of the model is high. The simulation results demonstrate that the method in this paper is superior in signal identification, the image signals can be better restored and enhanced and the PSNR of the restored image is enhanced.

2 Array Model Design

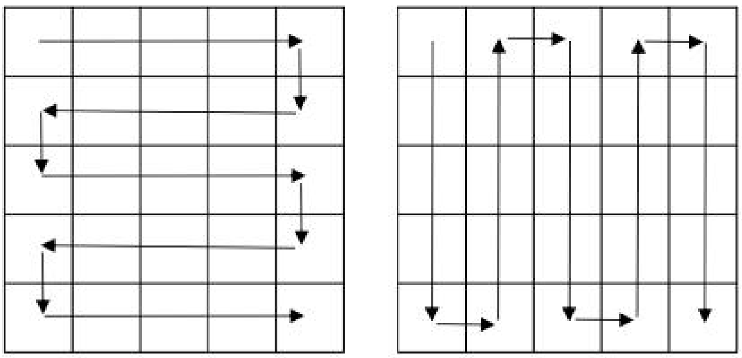
2.1 Adaptive SR Image Signal Identification Method

The adaptive saturating nonlinearity array model is presented under strong noise environment. In the experiment, the additive Gaussian white noise is adopted the to explore the feasibility of the method in the field of image signal recognition and image restoration. The steps of the saturating array model for image restoration in a strong noise environment are as shown below:

1) Reducing the image dimension and coding

By scanning in row order or column order, the two-dimensional image pixels are converted into a one-dimensional image sequence, as shown in Figure 1. The dimension reduction method of Figure 1(a) is row order scanning, which starts scanning from the element whose next row is closest to the last pixel value of the previous row. The dimension reduction method of Figure 1(b) is column order scanning, which starts scanning from the element whose next column is closest to the last pixel value of the previous column. Although the order of the two scanning methods is different, they can quickly and accurately reduce the dimension of the two-dimensional image.

This paper experiment uses column order scanning method, as shown in Figure 1(b). The two-dimensional image size is $2^k \times 2^k$. Then, original two-dimensional image matrix $T_{m\times n}$ is converted into a one-dimensional image sequence $J_{1\times mn}$. The one-dimensional image sequence $J_{1\times mn}$ values ranges from 0 to 255, with a total of 256 different digital sequences. Therefore, we encode the one-dimensional image sequence $J_{1\times mn}$ from 0 and 1 to get an 8-bit sequence of binary signal $H_{1\times 8mn}$.



(a) Row order scanning (b) Column order scanning

Figure 1 Array model scanning method

2) Modulation

The original grayscale image is reduced in dimension and binary encoded to obtain the binary symbol sequence $H_{1\times 8mn}$. The binary symbol sequence $H_{1\times 8mn}$ is further subjected to binary pulse amplitude modulation (BPAM) processing to obtain a one-dimensional bipolar non-periodic BPAM signal $r(t)$, the $r(t)$ expression is as follows:

$$r(t) = A\sum_{i=1}^{8mn} S_i W(t - kT_s), \tag{1}$$

where A represents the signal amplitude, m is the rows of the original grayscale image and n represents columns. $W(t)$ represents a rectangular pulse and its period is T_s, that is, when $t \in (0, T_s)$ $W(t)$ is 1 and while $t \notin (0, T_s)$ $W(t)$ is 0. S_i $(i = 1, 2, \cdots, 8mn)$ indicates a one dimensional signal sequence including -1 and 1 with polarity conversion on a binary sequence $H_{1\times 8mn}$ $(0 \to -1, 1 \to 1)$. The information on the 1D symbol sequence S_i obtained through image scanning, binary encoding and polarity conversion are independent random variables.

3) Stochastic resonance process based on adaptive saturating array

Now, signal $r(t)$ and noise $\xi(t)$ are applied to a nonlinear dynamic saturating system and perform stochastic resonance processing to restore the image. Each saturating nonlinearity[41−43] can be written:

$$\frac{dx_k(t)}{dt} = -\alpha x_k(t) + J\tanh[\beta x_k(t)] + r(t) + \xi(t), \tag{2}$$

where α, J and $\beta(\alpha > 0, J > 0, \beta > 0)$ are the system parameters of the saturating array SR processing model. $k = 1, 2, \cdots, N$, N is the size of system arrays, $r(t)$ is the input of the saturating nonlinearity, $x_k(t)$ is the propagation response for each signal, $\xi(t)$ is an independent and identically distributed Gaussian white noise with zero-mean and variance of ${\sigma_\xi}^2$.

The array model is shown in Figure 2. The saturating nonlinear system shown in Equation (4) in this paper is used as an array unit. Each array unit has a parallel processing structure and the input signals of each unit are independently and identically distributed, then the conditions for the stochastic resonance of each array unit and the nonlinear structural parameters of the array unit are the same. The one-dimensional noisy signal $g_k(t) = r(t) + \xi_k(t)$ is applied to each saturating array unit and $x_k(t)$ is the output of each nonlinearity. Then $X(t)$ is the overall output response and expression of the $X(t)$ is as follows:

$$X(t) = \frac{1}{N}\sum_{k=1}^{N} x_k(t). \tag{3}$$

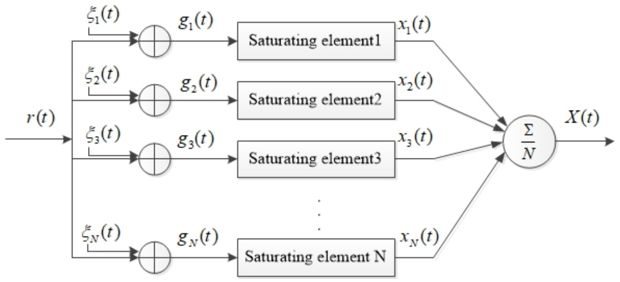


Figure 2 Block diagram of adaptive array saturating model

4) Demodulation and decoding

T_s represents the duration of each signal S_i, $t_i = iT_s$ represents the start time of each symbol. The demodulation method of $X(t)$ is written:

$$P_i = \mathrm{sign}(X(t_i + T_s)) = \begin{cases} 1, & X(t_i + T_s) \geq 0, \\ 0, & X(t_i + T_s) < 0, \end{cases} \tag{4}$$

then, the demodulated one-dimensional discrete signal $P_{1\times 8mn}$ is decoded to get a one dimensional sequence $V_{1\times mn}$ of 256 gray levels.

5) Recovering image

The one dimensional sequence $V_{1\times mn}$ can be converted into the restored grayscale image $Q_{m\times n}$ by the column anti-scanning method process.

2.2 The Index of Image Evaluation

The purpose for image restoration is to restore the degraded image so that the restoration result is as close as possible to the original image. Therefore, an objective evaluation index is needed to verify the quality of image restoration. The peak signal-to-noise ratio (PSNR)[44,45] is used as the quantitative evaluation index of the image restoration result via the mean-squared error (MSE) and its unit is dB. The PSNR is defined as follows:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right), \tag{5}$$

where the expression for MSE is defined as follows:

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(Q(i,j) - T(i,j))^2, \tag{6}$$

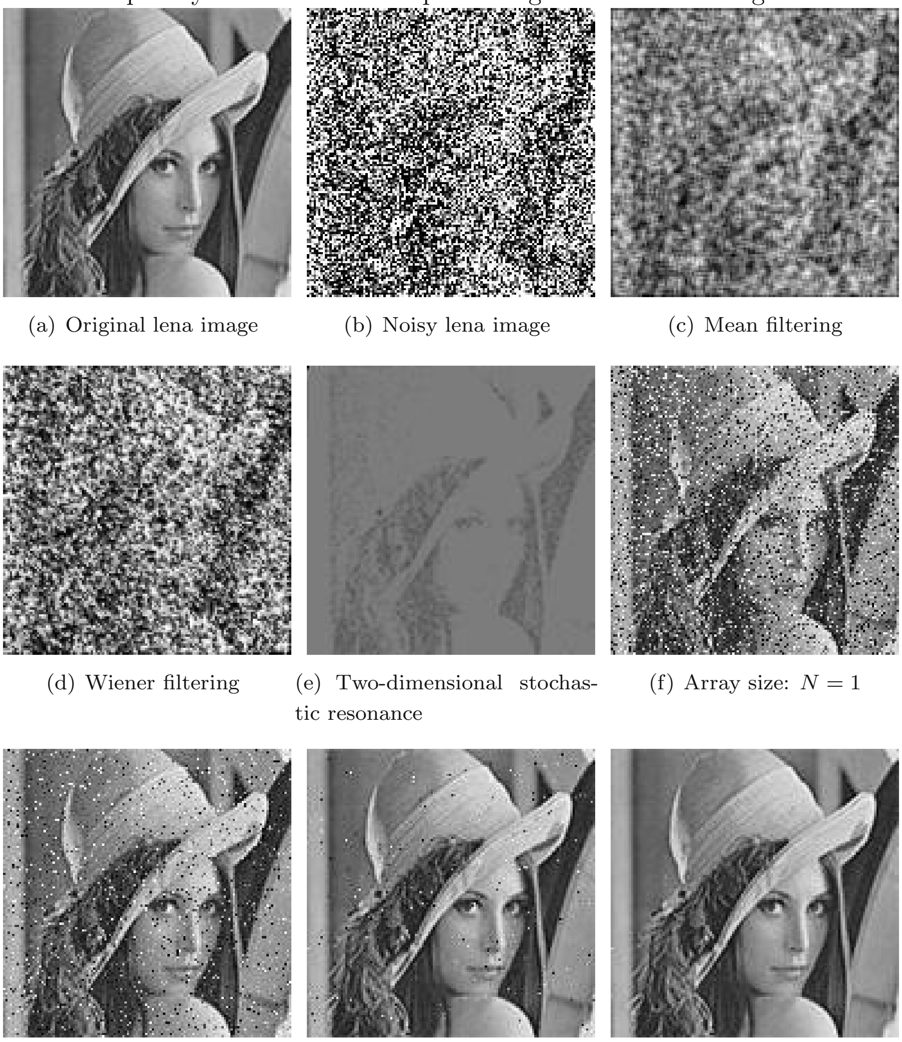
where the size of the gray image is m rows and n columns. $T(i,j)$ and $Q(i,j)$ represent the gray values of pixels in rows ird and jrd in the original images and in the restored images.

3 Performance Analysis and Simulation Results

After consulting a lot of references and comparing a lot of experimental results, the parameters of the saturating system in Equation (4) are as follows: $\alpha = 10000$, $J = 0.7$ and $\beta = 2.5$. In order to compare with the saturating array stochastic resonance image restoration method adopted in this paper, three traditional image restoration methods are selected, which are mean filter, Wiener filter and the two-dimensional stochastic resonance method. The saturating nonlinearity is used in the two-dimensional (2D) stochastic resonance method. The three traditional restoration methods have been optimized during the experiment comparison in this paper, and the experimental results are relatively good. In this paper, the specific parameter of the parallel array of saturating model is't only the array size N. The parameters of the saturating array model are optimized and fixed, and the size of N and the noise intensity are adjusted in the experiment. The Gaussian white noise is selected to add to the image. In this paper, when the noisy modulation signal is input to the saturating array unit, the synergy between noise, image modulation signal and nonlinear system causes stochastic resonance and suppresses the noise existing in the signal. The grayscale sense and visual effect of the experimental restoration image are superior, the PSNR value of the restored image is higher, a smaller error rate is obtained, and the enhanced effect of the restored image is remarkable. The following will analyze our experimental results.

3.1 Lena Image

The pixels size of the lena image is set to 128×128. The normalized Gaussian white noise with zero-mean and variance of 0.6 is added to the original lena image. Then, the PSNR of the lena image is PSNR=7.7309 dB. Figure 3 describes the comparison effect of the image restoration performance of the array model method proposed in this paper, mean filter, Wiener filter and the two-dimensional stochastic resonance method. As shown in Figure 3 (a)–(e), in the strong noise environment, the restored image is distorted, which process by the mean filter and the Wiener filter. The color of the restored image is dark and the gray level is not strong enough, which is processed by the two-dimensional stochastic resonance method. The processing effect of the traditional restoration method is not well. Figure 3 (f)–(i) show the restored lena image with the array size $N = 1, 2, 4, 10$. The grayscale constrast of the restored image is rapidly progressed. There are more black-and-white spots on the restored image with smaller array size as shown in Figure 3 (f)–(g). As the size of array increases, the noise black-and-white spots on the restored lena image becomes less gradually until the end, as shown in Figure 3 (h)–(i). It shows that comparing with the three traditional methods, the saturating array model is more superior in the processing of noisy signals. The increase in the size of the array makes the image restoration better, but as the size of the array increases, the computational complexity increases and the processing time becomes longer.



(a) Original lena image (b) Noisy lena image (c) Mean filtering

(d) Wiener filtering (e) Two-dimensional stochastic resonance (f) Array size: $N = 1$

(g) Array size: $N = 2$ (h) Array size: $N = 4$ (i) Array size: $N = 10$

Figure 3 Lena image restoration effect with different methods

Table 2 shows the PSNR performance comparison of mean filter, Wiener filter, the two-dimensional stochastic resonance method and saturating array stochastic resonance method. Comparing with the PSNR of the lena image with noise, the PSNR of the three traditional methods is increased slightly, the denoising effect is not obvious. In the saturating array model, the PSNR of the restored image can be enhanced with increasing the array size, that is, the effect of the restored image is better. With array size $N = 10$ the restored lena image is very approximate to the original image, the PSNR reaches 41.3681 dB.

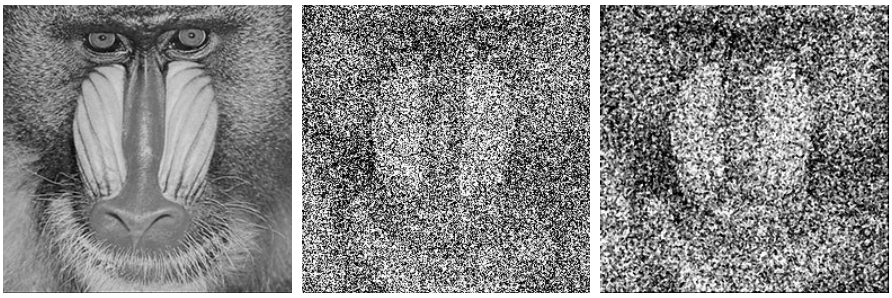
Table 2 The PSNR performance comparison of lena image (dB)

Image name	Image size	PSNR (dB)							
		Noisy lena	Mean method	Wiener method	2D stochastic resonance method	The proposed method			
						$N = 1$	$N = 2$	$N = 4$	$N = 10$
Lena	128×128	7.7309	14.8818	14.4104	15.4163	14.9822	19.6607	27.9134	41.3681

3.2 Mandrill Image

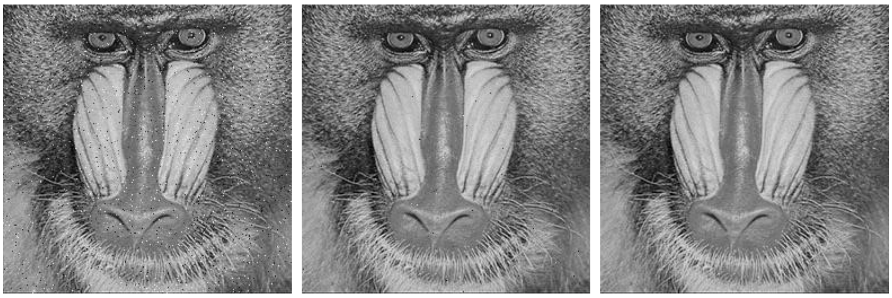
The pixels size of the mandrill image can be set to 256×256, the zero-mean Gaussian white noise with variance of 0.4 can be added to the mandrill image. Figure 4 shows the comparison of mandrill's restored images. As shown in Figure 4 (a)–(e), in the low PSNR environment, the image restoration effect of the traditional three image restoration methods is poor. Figure 4 (f)–(i) show the restored mandrill images obtained by the adaptive saturating array stochastic resonance method under different array sizes. The restoration result of the method in this paper is also slightly better in gray level, indicating that the restoration method in this paper effectively suppresses the noise.

It indicates that the PSNR of noisy mandrill image by the three traditional methods and the saturating array model in Table 3. It can be seen from Table 3 that the PSNR of images processed by mean filter and Wiener filter is small. When the array $N = 1$, the PSNR value obtained by the adaptive saturating array model and the two-dimensional stochastic resonance method for image restoration processing is slightly increased, but the image processing effect is not clear. The PSNR of the restored image can be increased with increasing the array size. When the array $N = 10$, the PSNR performance of the restored mandrill image is increased by about 33 dB. Experimental results show that the adaptive saturating nonlinearity array is superior in the grayscale image restoration process.



(a) Original mandrill image (b) Noisy mandrill image (c) Mean filtering

(d) Wiener filtering (e) Two-dimensional stochastic resonance (f) Array size: $N = 1$



(g) Array size: $N = 2$ (h) Array size: $N = 4$ (i) Array size: $N = 10$

Figure 4 Mandrill image restoration effect with different methods

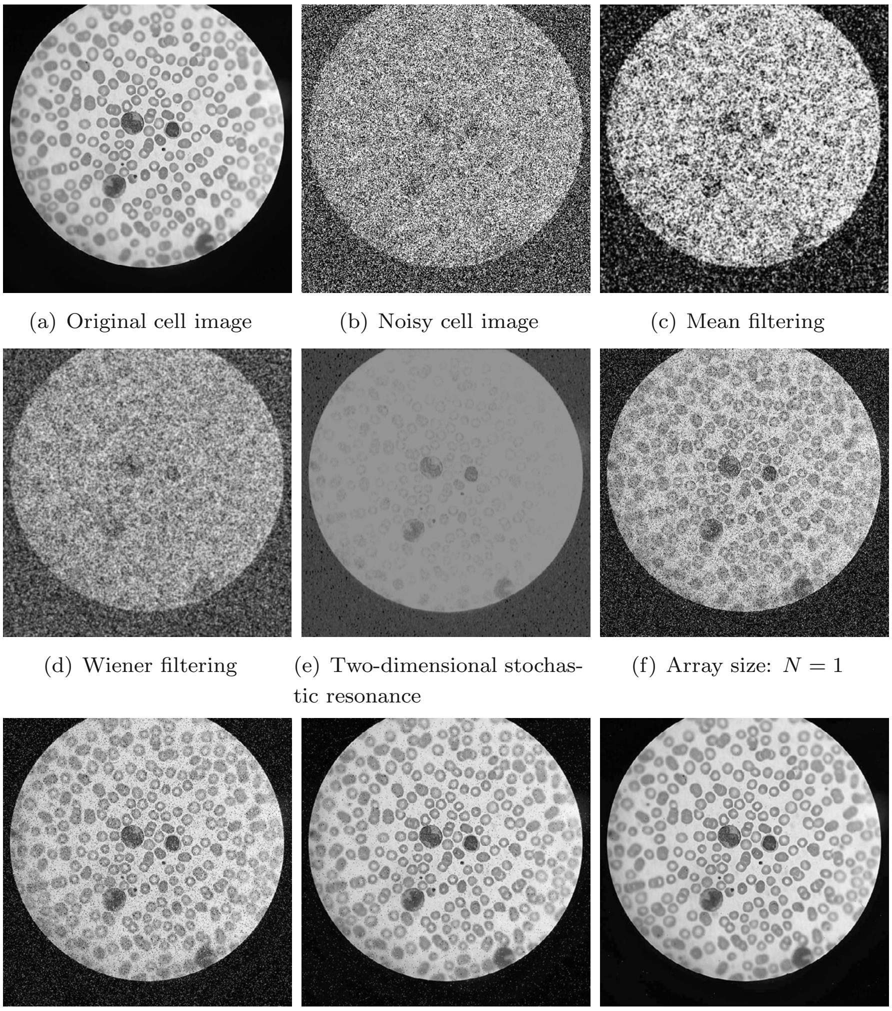
Table 3 The PSNR performance comparison of mandrill image (dB)

Image name	Image size	PSNR (dB)							
		Noisy mandrill	Mean method	Wiener method	2D stochastic resonance method	The proposed method			
						$N = 1$	$N = 2$	$N = 4$	$N = 10$
Mandrill	256 ×256	8.6709	15.8474	15.4637	18.2669	17.3855	23.9102	35.9837	42.0982

3.3 Cell Image

The pixels size of the cell image can be set to 512×512 and the normalized Gaussian white noise with zero-mean and variance of 0.8 is added to the original cell image. Therefore, the PSNR of the third cell image is 7.3799dB. Compared the visual effect of restoration performance in Figure 5 (c)–(f), it can be seen that the image denoising effect is not good and the details of the image are lost. However, as shown in Figure 5 (f)–(i), as increasing the array size, the restored image is gradually clear. When the array $N = 10$, comparing with the original cell image, the restored cell image still has few black-and-white spots. After the same saturating array unit processing, the restoration effect of the cell image is not ideal comparing with the restoration effects of the lena image and the mandrill image. Therefore, the restoration effect is related to the image size and noise intensity.

Table 4 demonstrates the PSNR performance comparison results of the processed cell images. It can be seen from Table 4 that when the array $N = 1$, the PSNR of adaptive saturating array model proposed in this paper is not much different from the PSNR value obtained by the traditional three image restoration methods. The PSNR of the restored image can be increased as increasing the array size and the effect of the restored image is clearer. With array size $N = 10$, the PSNR of the restores cell image has reach about 31 dB increment.



(a) Original cell image (b) Noisy cell image (c) Mean filtering

(d) Wiener filtering (e) Two-dimensional stochastic resonance (f) Array size: $N = 1$

(g) Array size: $N = 2$ (h) Array size: $N = 4$ (i) Array size: $N = 10$

Figure 5 Cell image restoration effect with different methods

Table 4 The PSNR performance comparison of cell image (dB)

Image name	Image size	PSNR (dB)							
		Noisy cell	Mean method	Wiener method	2D stochastic resonance method	The proposed method			
						$N=1$	$N=2$	$N=4$	$N=10$
Cell	512 ×512	7.3799	12.3794	12.1445	13.7334	13.8550	17.1189	23.6047	38.9367

3.4 Bit Error Rate

The bit error rate (BER) is an indicator that measures the accuracy of data transmission within a specified period of time, the BER expression is as follows:

$$\text{BER} = \frac{\sum xor(H(i,j), P(i,j))}{i \times j}, \tag{7}$$

where xor is a function, $H(i,j)$ represents the original binary symbol value in the i row and j column. $P(i,j)$ is the signal processed by the array system in the ird row and jrd column. Figure 6 shows the bit error rate curve of the mandrill image by adaptive array processing under different input variances. When there is only a single saturating system in the array model ($N = 1$), as the noise variance increases, the signal is submerged in the noise, and the signal in the transmission process cannot be effectively recognized by the saturated system, so the bit error rate of the system output signal increase. But when the array size increases ($N > 1$), compared with a single saturating system, the system bit error rate has been further reduced. The above results show that the adaptive saturating array model can effectively reduce the bit error rate of the signal, and has important significance for the enhanced detection of weak signals under strong noise background.

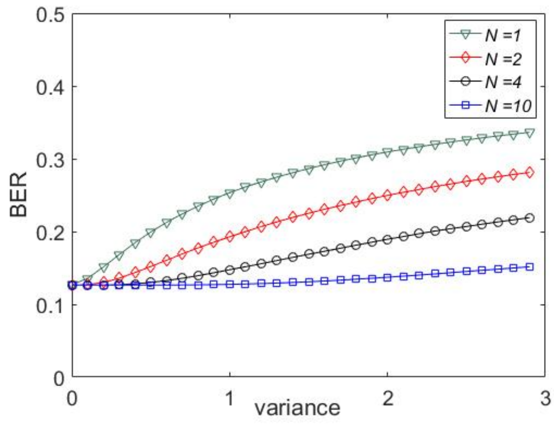


Figure 6 Best bit error rate curve

3.5 Improvement Signal-to-Noise Rate

The improvement signal-to-noise ratio factor (ISNR) is an indicator of the noise suppression of the processing method. If the ISNR value is negative, it means that the noise is suppressed after processing. The lower the ISNR value, the better the processing effect, the ISNR expression is as follows:

$$\text{ISNR} = 10 \times \log_{10}\left(\frac{\text{sum}(\text{sum}(Q-T)^2)}{\text{sum}(\text{sum}(R-T)^2)}\right), \tag{8}$$

where T is the original gray image, R is the noise pollution image, and Q is the restored gray image. Table 5 shows the ISNR values of lena image, Mandrill image and cell image under different image denoising processing methods. It can be seen from Table 5 that the Wiener filtering and the mean filtering have the same noise suppression conditions. The two-dimensional stochastic resonance method and the saturating array model $N = 1$ have the same noise suppression conditions. However, as the array size increases, the noise suppression is more effective and the lower the ISNR value.

Table 5 ISNR values of different image restoration methods (dB)

Image restoration method	ISNR (dB)		
	Lena image	Mandrill image	Cell image
Wiener filtering	−12.1062	−6.6737	−20.1535
Mean filtering	−9.2112	−8.0688	−19.7581
2D stochastic resonance method	−12.6555	−12.1442	−21.4990
array $N = 1$	−12.0821	−12.5500	−20.9612
array $N = 2$	−16.4266	−18.4757	−24.5813
array $N = 4$	−23.8576	−25.9962	−30.7665
array $N = 10$	−32.2007	−27.0478	−45.3582

4 Conclusion

In this paper, a signal identification method for correlated noise images based on adaptive array stochastic resonance is proposed. By designing the processing structure of the parallel uncoupled saturating array system, the accuracy of image signal identification is improved and the image restoration effect is better. The influence of the noise interference signal strength and the size of the system array to the signal error rate is analyzed, and it is shown that the method of this paper can accurately identify the image signal under strong signal interference. The simulation results show that compared with the processing results of a single saturating system, the array stochastic resonance system is more accurate and efficient in removing noise interference signal processing, and it can identify the correct image signal. As the size of the array increases, the signal recognition rate is higher, that is, the effect of restoring the image is more obvious. The method proposed in this paper can effectively enhance the visual effect of grayscale images disturbed by noise, and it is more significant in the improvement of PSNR and gray level. Therefore, the model in this paper has potential application prospects in the fields of image communication systems, aerospace technology, medical diagnosis and crop production status.

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