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A New Wavelet Thresholding Method Based on Cyclostationarity for Enhancing the Interception of Computer Video Leakage Signals

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***Abstract*—Computer displays emit electromagnetic waves, which leak the information displayed by the computers. Electromagnetic radiation signals from computer displays can be a security risk if they are intercepted and reconstructed. Signal to noise ratios (SNR) of video leakage signal are usually low due to the environmental noise and many other man-made noises. This can seriously influence the quality of the reconstructed image and further processing of video leakage signals. In this paper, a new cyclostationarity wavelet thresholding method is proposed for enhancing the interception of the video leakage signals by improving the SNR of signals. We analyzed the cyclostationarity property of computer video leakage signals, and then we used that property to improve the performance of wavelet thresholding method and the performance of pre-processing computer video leakage signals. We pre-processed one-dimensional leakage signals without reconstructing the image in order to process signals more efficiently. At the same time, the performance of processing image can also be improved as long as the processed signal can be reconstructed to an image. The processed results of the actual experimental data show that the proposed algorithm performs better both on denoising one-dimensional signal and two-dimensinal reconstructed image than the other four wavelet thresholding methods which are Square-Root-Log, Minimax principle, Heursure and Rigrsure.**

***Index Terms*—information security,information leakage, information interception , signal denoising, wavelet transform.**

I. Introduction

Computer displays emit electromagnetic waves which leak the information displayed by the computers. Confidential information might be leaked if someone intercepts these leakage video signals and reconstructs the display image [1]. This can be a potential information security threat as the sensitive information can be stolen from a distance without leaving any trace. Electromagnetic radiation was mentioned in some papers as a computer security risk [2,3].

SNRs of received video leakage signals are usually low due to the environmental noise and many other man-made noises. This can seriously influence the quality of the reconstructed image and further processing of video leakage signals, such as for the detection and identification. Some works use image processing method to denoise the reconstructed image [4]. These methods can be called as post-processing of leakage signals since the signals are processed after reconstructing an image. These works are based on the reconstructed image, but to correctly reconstruct the electromagnetic radiation signal, the horizontal synchronizing information is essential. However, the synchronization information of the computer is unknown in practical non-cooperative attack scenarios. Extra work is required to extract synchronization information and change the original one-dimensional signal into an image [5,6]. It is inefficient, especially when the number of signals is very large. Wavelet is a time-frequency analysis that is used to denoise the non-stationary signals such as video leakage signals. The selection of the threshold is the most significant and difficult part of wavelet analysis. To solve these problems, considering that the video leakage signals show a cyclostationary property, we propose a new threshold wavelet denoising method based on the cyclostationarity of video leakage signals.

The main goal of our work is to enhance the interception of the video leakage signals by improving the SNR of signals. We focus on pre-processing of one-dimensional leakage signals without reconstructing the image in order that we can to process signals more efficiently. In addition, the proposed algorithm can also denoise the reconstructed image if the processed one-dimensional signal can be reconstructed into an image. In this paper, we analyzed the cyclostationarity property of video leakage signals and then we propose to use the cyclostationarity of video leakage signal to choose the wavelet threshold. A direct signal to noise ratio (SNR) cannot be measured. Therefore, another metric called quasi signal to noise ratio (QSNR) is defined to estimate the quality of signal to noise ratio of video leakage signals. Finally, via sampling and processing the experimental data, we demonstrate the performance of the proposed cyclostationarity threshold algorithm and compare it with four other wavelet thresholding methods which are Square-Root-Log, Minimax principle, Heursure and Rigrsure.

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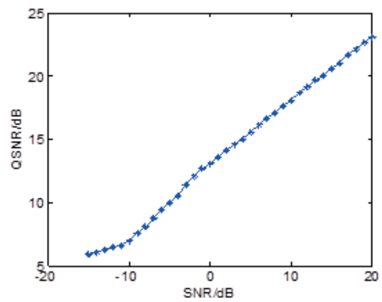

Fig. 1. Simulation of SNR and QSNR.

II. Cyclostationarity wavelet thresholding method

A. Quasi signal to noise ratio (QSNR)

In the proposed algorithm, the signal to noise ratio (SNR) needs to be estimated. The normal estimation formula of SNR is as follows,

$$SNR = 10log_{10}(\frac{Signal\ Power}{Noise\ Power}) \tag{1}$$

Since the received signal is mixed with noise, it is difficult to calculate the signal power and noise power respectively. In [7] while working on denoising evaluation of an image, they used the ratio of maximum and minimum local variance to be similar to peak signal to noise ratio (PSNR). Inspired by this, we propose to use the ratio of maximum and minimum local variance as the indication of SNR. We call this metric as quasi SNR (QSNR) and define it as,

$$QSNR = max(\sigma_i^2)/min(\sigma_i^2) \tag{2}$$

where,

$$\sigma_i^2 = \sum_{m=-R}^{R} \left[x(i+m) - \mu_i\right]^2 / (2R+1)) \tag{3}$$

where,R is the local window which can be chosen according to signal length. μ_i is the average value.

$$\mu_i = \sum_{m=-R}^{R} x(i+m)/(2R+1)) \tag{4}$$

To verify QSNR, we compared SNR and QSNR by simulating a pure signal and plus some random noise on it. The result is shown in Fig.1. The horizontal axis is SNR and vertical axis is QSNR. Fig.1 shows that there is a linear relationship between SNR and QSNR. Since we focus on the relative change of SNR rather than the absolute value of SNR, it is feasible to estimate the SNR by calculating QSNR.

B. Cyclostationarity wavelet thresholding method

The wavelet threshold method has one obvious disadvantage; it is difficult to choose the threshold. In this paper, we propose to use the cyclostationarity of video leakage signals to choose the threshold.

Video leakage signal shows cyclostationary property because there are many frames in the video signals and signals of each frame are the same. Thus, video leakage signals can be modeled as a cyclostationary process. The signals shown in the cycle frequency domain is the signal we want, so the threshold value can be obtained in the cycle frequency domain. In addition, the rationale behind this approach is that the value of the cyclic spectrum density is the average value of the signal in the specific cycle frequency. Thus, the minimum value of the cyclic spectrum density can be seen as the threshold of the video leakage signals. The specific algorithm is as follows.

Firstly, compute the wavelet coefficients of the video leakage signals.

$$s \xrightarrow{DWT} \{a_L, d_j\} \tag{5}$$

where s is the initial electromagnetic radiation signal. $\{a_L, d_j\}$ are the wavelet coefficients. DWT of a signal $s(t)$ is given by [8]

$$W(l,m) = \int_{-\infty}^{\infty} 2^{l/2}\varphi(2^l t - ms(t))dt \tag{6}$$

where l is the discrete translation and m is the discrete dilations.
Secondly, compute the cyclic spectrum density $S_x^\alpha(f)$ of the wavelet coefficients.

$$S_x^\alpha(f) = F\left\{R_x^\alpha(\tau)\right\} = \int_{-\infty}^{+\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \tag{7}$$

$$R_x^\alpha(\tau) = \lim_{T\to\infty} \int_T x(t+\tau/2)x(t-\tau/2)^* e^{-j2\pi\alpha t} dt \tag{8}$$

Thirdly, we segment $S_x^\alpha(f)$ into N different signal segments $S_{xi}^\alpha(f), i = 1, 2, ..., N$. Then we compute the mean of the minimum value of the $S_{xi}^\alpha(f)$ as the threshold.

$$Thr = \frac{1}{N}\left(\sum_{i=1}^{N} min(S_{xi}^\alpha(f))\right) \tag{9}$$

Then, process the signal with the hard or soft thresholding method. The hard processing procedures can be represented by equation (12) and the soft processing procedures can be represented as equation (13).

$$\left\{\tilde{a_L}, \tilde{d_j}\right\} = \begin{cases} 0, |\{a_L, d_j\}| < Thr \\ \{a_L, d_j\}, \{a_L, d_j\} \geqslant Thr \end{cases} \tag{10}$$

$$\left\{\tilde{a_L}, \tilde{d_j}\right\} = \begin{cases} 0, |\{a_L, d_j\}| < Thr \\ sign\left(\{a_L, d_j\}\right)\left(|\{a_L, d_j\}| - Thr\right), \{a_L, d_j\} \geqslant Thr \end{cases} \tag{11}$$

where, $\{a_L, d_j\}$ are the wavelet coefficients.$\left\{\tilde{a_L}, \tilde{d_j}\right\}$ are the effective coefficients.

Finally, we perform the inverse wavelet transformation to get the output signal $\tilde{X}$.

$$\left\{\tilde{a_L}, \tilde{d_j}\right\} \xrightarrow{IDWT} \tilde{X} \tag{12}$$

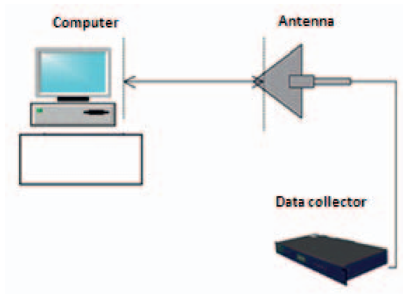

Fig. 2. Measurement setup for data collection.

TABLE I
VALUES OF THE QSNR FOR THE ORIGINAL SIGNAL AND PROCESSED SIGNAL

original signal	signal processed by the proposed algorithm
11.3	25.02

III. EXPERIMENTS

In this section, the proposed cyclostationarity wavelet thresholding method was applied to experimental data. The measurement setup is shown in Fig. 2. The resolution of the computer LCD display was set at 1024×768. A log-periodic antenna (ZN30505E) designed for 30-3000 MHz was placed in front of the surface of the tested computer and its height was the same as the height of the computer display center. It's important to note that we placed the antenna 1m-10m from the tested computer to obtain signals. The antenna distance can influence the SNR of received signals. The performance of the algorithm under different SNR caused by different antenna distance is presented in Section 4. The antenna was connected to a data collector, which can be data acquisition card, digital oscilloscope and spectrum analyzer. A spectrum analyzer was used here. As for sample frequency, according to the VESA standard [9], the range of pixel frequency is from 31.5MHz to 297MHz. When the resolution of the computer is 1024×768, the range of pixel frequency is from 44.9MHz to 94.5MHz. Considering that these video interface signals include harmonics of the fundamental signal frequency, we chose 500MHz as the sample frequency.

The original signal in time domain is shown in Fig.3 and the signal denoised by proposed method in time domain is shown in Fig.4. It can be seen that the noise in Fig.4 is less than that of the signal in Fig.3.

We estimated the SNR for Fig.3 and Fig.4 by calculating QSNR with the formula of (2). After experimentation, we chose 10 as the local window . Table 1 shows the values of the QSNR for the original signal and processed signal. We performed this thresholding method by using hard thresholding method and chose the db1 wavelet. It can be observed from this table that the QSNR of the processed signal is higher than the QSNR of the original signal.

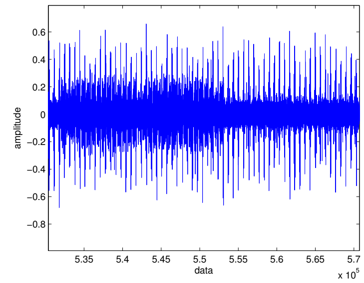

Fig. 3. Original signal in time domain.

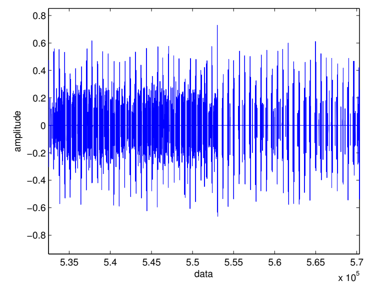

Fig. 4. Signal in time domain denoised by cyclostationarity wavelet threshold method.

IV. DIFFERENT METHODS COMPARISON

To evaluate the proposed cyclostationarity wavelet thresholding method, a comparative analysis of four other wavelet thresholding methods have been used. The four methods are Square-Root-Log (sqtwolog), Minimaxi using minimax principle, Heursure and Rigrsure using the principle of Stein Unbiased Risk Estimate (SURE). These methods, as described in [10], are as follows:

- Sqtwolog criterion

It can be calculated from the universal thresholding method using the median absolute deviation σ and the length N_j of the noisy signal at the jth scale as in [8]:

$$\sigma_j = Median(|\omega|)/0.6745 \tag{13}$$

$$th_j = \sigma_j \sqrt{N_j} \tag{14}$$

where ω represent the wavelet coefficient at scale j.

- Rigrsure criterion

A soft thresholding method evaluator of unbiased risk. It can be calculated as follows,

$$th_j = \sigma_j \sqrt{\omega_b} \tag{15}$$

where ω_b is the bth squared wavelet coefficient at minimum risk chosen from the vector $W = [\omega_1, \omega_2, ..., \omega_N,]$ which contains the square wavelet coefficient values that are arranged from small to large and σ is the standard deviation of the noisy signal.

TABLE II
VALUES OF THE QSNR FOR WAVELET METHOD BY SELECTING DIFFERENT THRESHOLDS

Methods	SWT	cyc	heursure
hard threshold	sym6	**26.11**	**23.45**
	db1	**25.02**	**22.03**
	Coif2	**27.95**	**24.58**
soft threshold	Sym6	**29.57**	**26.12**
	db1	**27.81**	**24.51**
	Coif2	**29.67**	**26.30**
Methods	**rigrsure**	**sqtwolog**	**minimaxi**
hard threshold	**17.89**	**16.32**	**14.29**
	16.04	**14.01**	**13.21**
	19.57	**18.23**	**15.46**
soft threshold	**20.98**	**18.96**	**17.52**
	18.27	**16.37**	**15.02**
	21.65	**20.14**	**17.56**

TABLE III
VALUES OF THE QPSNR FOR WAVELET METHOD BY SELECTING DIFFERENT THRESHOLDS

Methods	SWT	cyc	heursure
hard threshold	sym6	**24.13**	**20.79**
	db1	**26.59**	**22.10**
	Coif2	**23.01**	**19.63**
soft threshold	Sym6	**25.12**	**21.59**
	db1	**27.32**	**23.68**
	Coif2	**24.26**	**21.89**
Methods	**rigrsure**	**sqtwolog**	**minimaxi**
hard threshold	**20.74**	**18.54**	**17.89**
	23.65	**21.74**	**19.98**
	18.21	**17.3**	**15.24**
soft threshold	**21.96**	**19.68**	**18.25**
	24.21	**22.25**	**20.13**
	20.78	**19.56**	**17.87**

- Heursure criterion

It is a combination of both Sqtwolog and Rigrsure methods. When signal to noise ratio is very small, the SURE method of estimation is poor whereas the Sqtwolog method gives better threshold estimation.

- Minimax criterion

It based on the minimax principle that is used in statistics. A fixed threshold is used to yield the minimax performance for mean square error against an ideal procedure.

We performed these thresholding methods by using hard and soft thresholding methods respectively. We estimated SNR by calculating QSNR with equation (2). After experimentation, we chose 10 as the local window R. In order to evaluate the performance of the different thresholding methods, we selected different mother wavelet functions from different families including daubechies (db1-db20), symlet (sym1-sym20) and coiflet (coif1-coif5). We selected sym6, db1 and coif2 as the representation of the three mother wavelet functions families. We performed the hard thresholding method and the soft thresholding method for the selected mother wavelet functions. Table 2 shows the values of the QSNR for these thresholding methods. In the Table 2, "cyc" means the proposed cyclostationarity thresholding method and the QSNR of initial signal is 11.3. It can be seen from the Table 2 that the proposed cyclostationarity thresholding method has the highest value of QSNR in every mother wavelet function.

Furthermore, although the main goal of this paper is to improve the SNR of the received one-dimensional signal, we can also evaluate the proposed algorithm by checking the effect of image denoising. To evaluate the result, the video leakage signal was reconstructed. The computer's synchronization information was obtained by using the method proposed in [11]. Fig.5 gives the image shown in the PC. The reconstructed image at the original leakage signal is shown in Fig.6 and it is worth noting that the two vertical lines shown in the reconstructed image are the synchronization signals. The image reconstructed at the final output signal denoised by the proposed method is shown in Fig.7. The images reconstructed at the final output signals denoised by the other four methods are shown in Fig.8-11. It can be seen that Fig.7 contains the least noise among the images. This means that the proposed cyclostationarity thresholding method has a better denoising ability than the other four thresholding methods.

We use the ratio of maximum and minimum local variance as the indication of peak signal to noise ratio (PSNR) [9]. The quasi PSNR can be called as QPSNR.

$$QPSNR = \underset{x,y}{max}\sigma^2_{(x,y)}/\underset{x,y}{min}\sigma^2_{(x,y)} \quad (16)$$

where,

$$\sigma^2_{(i,j)} = \sum_{k=-P}^{P}\sum_{l=-Q}^{Q}\left[F(i+k,j+l)-\mu_{(i,j)}\right]^2/(2P{+}1)(2Q{+}1) \quad (17)$$

$$\mu_{(i,j)} = \sum_{k=-P}^{P}\sum_{l=-Q}^{Q}F(i+k,j+l)/(2P+1)(2Q+1) \quad (18)$$

In order to evaluate the performance of the different thresholding methods, we selected sym6, db1 and coif2 as the representation of the three mother wavelet functions families. We performed the hard thresholding method and the soft thresholding method for the selected mother wavelet functions. The results of QPSNR are shown in Table 3. In this Table 3, "cyc" means the proposed cyclostationarity thresholding method and the QPSNR of initial signal is 11.62. It can be seen from the Table 3 that the proposed cyclostationarity thresholding method has the highest value of QPSNR in every mother wavelet function.

Then, we tested 200 sets of signals to evaluate the performance of the proposed cyclostationarity threshold algorithm. In addition, the distance between antenna and tested computer can affect SNR, which decreases as the distance increases. Thus, we analyzed the performance of the cyclostationarity threshold algorithm and the other threshold algorithms under different SNR by increasing the distance. The results of these

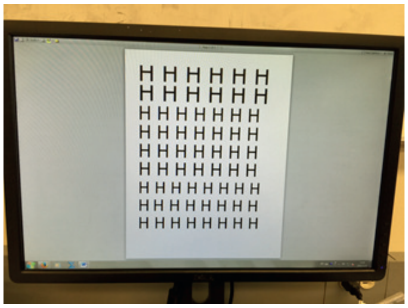

Fig. 5. Image shown in computer display

Fig. 6. Image reconstructed with initial leakage signals.

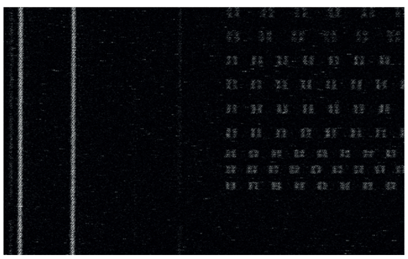

Fig. 7. Image reconstructed with signals denoised by cyclostationarity thresholding method.

experiments are shown in Figs.12 and 13. Fig.12 gives a comparison based on the signal quality at the output of the algorithms using db1 hard thresholding method with different thresholds, revealing the effect of the proposed algorithm. The vertical and horizontal axes of Fig.12 are the average values of output and input QSNR of the 200 sets of signals. Fig.13 gives a comparison based on the reconstructed image qualities. The vertical and horizontal axes of Fig.13 are the average values of output and input QPSNR of the 200 sets of images which were reconstructed by processed signals using the sym6 hard thresholding method with different thresholds.

The results revealed that both one-dimensional signals and reconstructed images processed with the proposed cyclostationarity thresholding algorithm has better quality than the ones processed with the other thresholding algorithms.

V. Conclusion

To enhance the interception of video leakage signals, a novel signal pre-processing algorithm is proposed. We focused

Fig. 8. Image reconstructed with signals denoised by Heursure thresholding method.

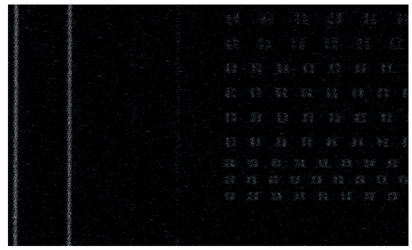

Fig. 9. Image reconstructed with signals denoised by Rigrsure thresholding method.

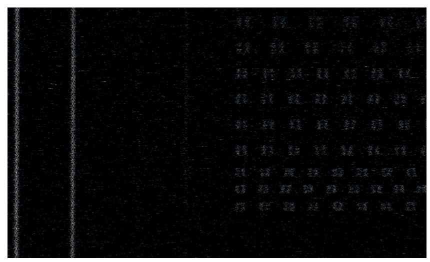

Fig. 10. Image reconstructed with signals denoised by Sqtwolog thresholding method.

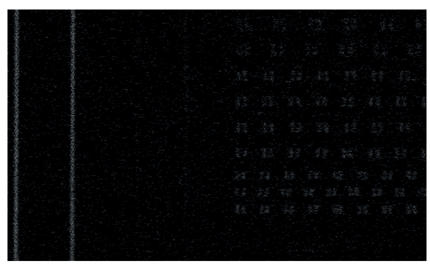

Fig. 11. Image reconstructed with signals denoised by Minimaxi thresholding method.

on improving the SNR of received one dimensional signals without reconstructing the images since it is inefficient to do extra work to reconstruct the image.

After analyzing the cyclostationarity property of computer video leakage signals, we proposed a new cyclostationarity wavelet thresholding method for improving the SNR of computer video leakage signals. We solved the problem of selecting threshold in processing video leakage signal by using the wavelet thresholding method. Since a direct SNR cannot

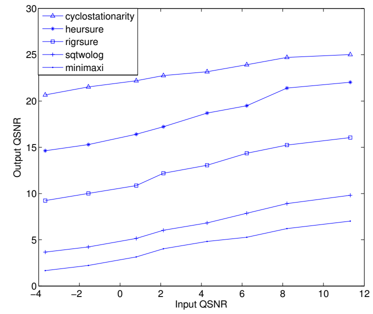

Fig. 12. Output QSNR vs. input QSNR for one-dimensional signal using db1 hard thresh method.

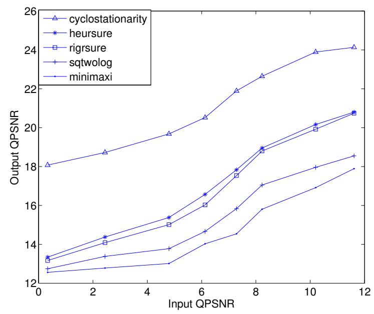

Fig. 13. Output QPSNR vs. input QPSNR for reconstructed image using sym6 hard thresh method.

be measured in the situation of this paper, we defined the quasi signal to noise ratio (QSNR) to estimate the SNR of video leakage signals. Finally, via sampling and processing our experimental data, we demonstrated that the proposed cyclostationarity wavelet thresholding algorithm performs better on denoising one-dimensional video leakage signals than the other four wavelet thresholding methods (Square-Root-Log, Minimax principle, Heursure and Rigrsure).

It's worth mentioning that, although our main goal is to improve the SNR of one-dimensional signals, the proposed cyclostationarity wavelet thresholding algorithm method can also denoise the reconstructed image if the processed one-dimensional signal can be reconstructed into an image. Furthermore, the experimental data demonstrated that the denoising image ability of the proposed algorithm is also superior to the other four algorithms.

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