Research of Blind Watermark Detection Algorithm Based on Generalized Gaussian Distribution

Xiang-wei Zhu
Suzhou Campus, Nanjing Institute of Railway Technology, Suzhou, China
Email: zxwook@163.com

***Abstract*— In digital management, multimedia content and data can easily be used in an illegal way-- being copied, modified and distributed again. Copyright protection, intellectual and material rights protection for authors, owners, buyers, distributors and the authenticity of content are crucial factors in solving an urgent and real problem. In such scenario, digital watermark techniques are emerging as a valid solution. Blind watermark detection is a modern digital watermark technology with outstanding feature. A novel algorithm of Blind Watermark Detection based on Generalized Gaussian Distribution is proposed in this paper. To start with, this paper carries on the statistical analysis to the high frequency sub-band coefficients of wavelet and contourlet transform, then knowing the high frequency sub-band coefficients of wavelet and contourlet transform can be characterized by Generalized Gaussian Distribution. So a blind watermark detection algorithm can be designed according to the method of maximum likelihood estimator. Experimental results demonstrate that the performance of watermark detector is good based on Generalized Gaussian Distribution. The scheme is robust against most attack, so it is very effective and practical.**

***Index Terms*—Wavelet Transform, Contourlet Transform, Generalized Gaussian Distribution, Maximum Likelihood Estimator, Blind Watermark Detection**

I. INTRODUCTION

The digital product may very easily be duplicated by the illegal method on Internet, so the copyright owner's rights and interests cannot be effectively protected. Therefore the research of digital product copyright protection has the vital practical significance. Digital watermark is the technique to protect the copyright of the digital product, and called as the last line of defense for the digital product copyright protection [1].

The three key technologies of digital watermark are the technology of generated watermark information, the watermark embedded algorithm and the watermark detection (extraction) algorithm. The watermark algorithm can be divided into two kinds according to watermark detection process in whether to use the original image.

①When detection needs the original image, this kind of algorithm usability is not strong.

②When detection does not need the original image and the original watermark, namely blind watermark algorithm. The majority situations is unable to obtain the original image to carry on the detection, therefore, the blind watermark algorithm is the current watermark engineering research hot spot, and it has the more widespread application prospect.

A digital watermark is a method that embeds a watermark in a digital media by making small changes in the digital media. The embedded watermark must be perceptually invisible and it must be difficult to change or remove it against the intentional or unintentional attacks. A blind watermark algorithm based on Generalized Gaussian Distribution is proposed in this paper. The algorithm does not need the original image and the original watermark information, so it is really meaning blind watermark detection. The results of experiment prove that the blind watermark detection has the very good examination performance.

II. WAVELET AND CONTOURLET TRANSFORM

The watermark techniques are classified into either spatial or transform domain techniques. Space domain methods hide information by changing space domain characteristic of host image; while transform domain methods by changing some coefficients of transform domain of host image, then the watermarked image is obtained by inverse transform. The popular watermark algorithms of transform domain include Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT) and so on [2].

In recent year, the new technology of Contourlet transform is applied in the watermark fields. The technologies of Wavelet transform and Contourlet transform domain are applied in this paper to fulfill watermark embedded and blind detection.

A. Wavelet Transform

Wavelet transform to image is converted into low-frequency domain (on behalf of the general picture of the image) and the high frequency domain (on behalf of the details of the image). The images of high-frequency domain can be divided into horizontal component of HL, the vertical component of LH and the Diagonal direction component of the HH. If the low-frequency domain for

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further wavelet decomposition, the low-frequency domain will be in accordance with the above-mentioned principles of recursive generate a higher level of high frequency and low frequency domain [3]. After wavelet transform to image, which has been divided into different sub-band frequency space structures with Figure 1 shows the three-level sub-band image of wavelet transform about the image of 512×512 baboon.

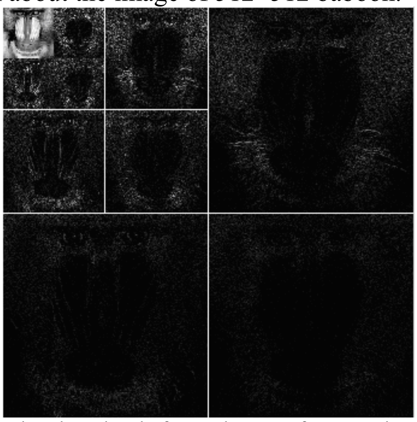


Figure 1 The Three-level of Wavelet Transform on The Image of 512×512 Baboon

The image includes the low-frequency sub-band image, the three high frequency sub-band images of the first level, the three high frequency sub-band images the second level and the three high frequency sub-band images the third level.

Figure 2 demonstrates the three levels of Wavelet Transform sub-bands, which are the low-frequency direction sub-band(LL3) and the three-level high-frequency direction sub-band (HLi,LHi,HHi;i=1,2,3).

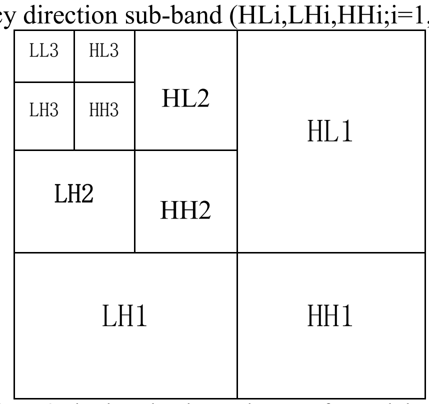


Figure 2 The three-level Wavelet Transform sub-bands

B. *Contourlet Transform*

Candes and Donoho in 1999 proposed that non-auto-adapted Curvelet transform [4]. This indicated that the image the non-auto-adapted sparse expression is possible. In 2003, M.N.Do and M.Vetterli constructed one kind of new non-auto-adapted multi-direction and multi-criterion Contourlet transform based on the idea of the Curvelet transform. M.N.Do and M.Vetterli constructed one kind of multi-scale and multi-direction decomposition using a combination of a Laplacian pyramid (LP) and a directional filter bank (DFB). Band-pass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double iterated filter bank structure, named contourlet filter bank, which decomposes images into directional sub-bands at multiple scales [5]. The LP and the DFB union form the double-tier group structure, which is called tower-shaped directional filter group PDFB. Their work leads to an effective method to implement the discrete curvelet transform. Because this transform approaches the original image by the contour section, therefore this is called the Contourlet transform.

Figure 3 shows multi-scale and multi-direction decomposition using a combination of a Laplacian pyramid (LP) and a directional filter bank (DFB).

Figure 4 shows the image of three-level Contourlet transform about the image of 512×512 baboon. The image includes the image of low frequency sub-band, the images of the four high frequency sub-bands in first level, the images of the eight high frequency sub-bands in second level and the images of the sixteen high frequency sub-bands in third level.

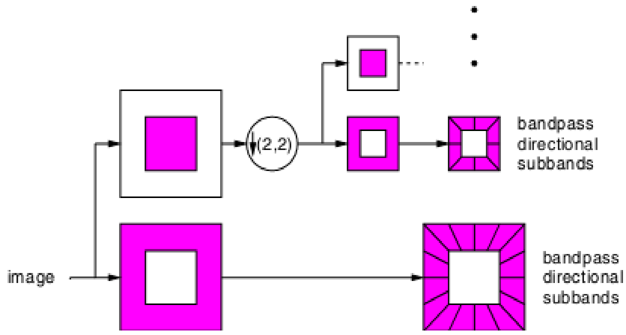


Figure 3 Theory of Contourlet Transform

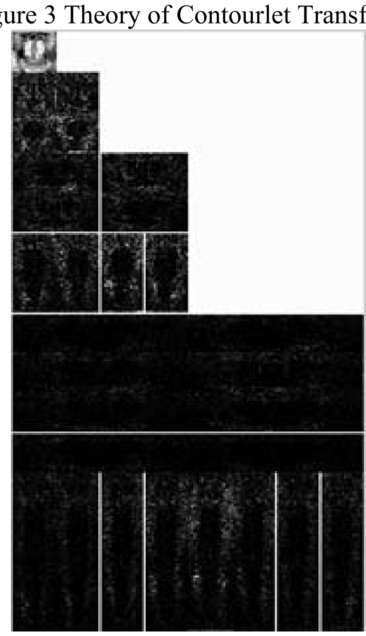


Figure 4 The Three-level Contourlet Transform on The Image of 512×512 Baboon

III. GGD(Generalized Gaussian Distribution)

As shown in Figure 1 and Figure 4 for the three-level wavelet and contourlet transform on the image of 512 × 512 Baboon, The statistical histogram of each high frequency sub-band coefficients is same as shown in Figure 5.

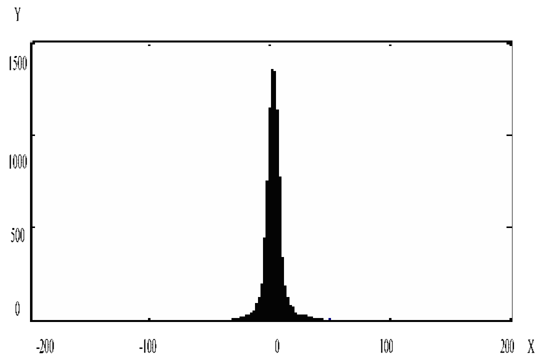


Figure 5 High Frequency Sub-Band Coefficients Histogram

The high peak value is around the zero value, and both sides of the high peak value are the length trailing. Namely, the majority values of direction sub-band coefficients are zero, only few value of sub-band coefficients are great. So each high frequency sub-band coefficients of Wavelet and Contourlet transform conforms to GGD(Generalized Gaussian Distribution) by the way of mathematical statistics. This conclusion for the blind watermark detection has laid the rationale.

The GGD's probability density function shows as flowing equation. [6]

$$p\left(x;\mu,\nu\right)=\frac{\nu}{2\mu\Gamma\left(1/\nu\right)}\exp\left(-\left|x\right|/\mu\right)^{\nu} \qquad (1)$$

In equation (1), μ is the GGD scale parameter, uses it to control p(x; μ, ν) width; ν is the GGD shape parameter, uses it to control p(x; μ, ν) shape, $\Gamma\left(x\right)=\int_0^{+\infty} e^{-t}t^{x-1}dt$ is the gamma function.

When $\nu = 1$ and $\nu = 2$, GGD is respectively called as the Laplacian distribution and Gaussian distribution. Figure 6 shows the Generalized Gaussian Distribution (from top to bottom, the value of ν is respectively equal 3,2.5,2,1.5,1,0.5,0.2). When $0 < \nu < 1$, the curve is heavy-tailed distribution. When $\nu \to \infty$, the curve is close approximation for the uniform random distribution.

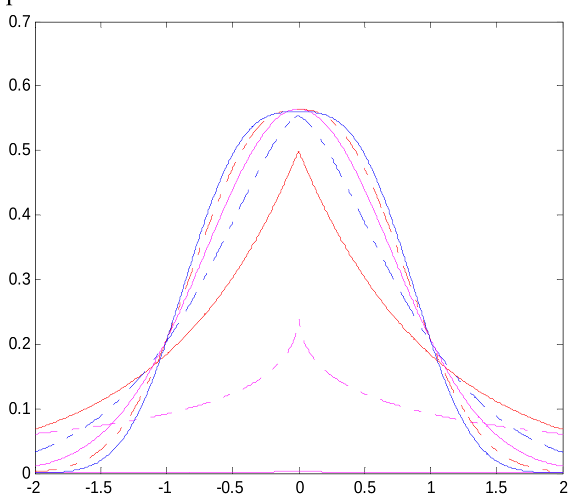


Figure 6 GGD Diagram of Different Shape Parameter

Ⅳ. Watermark Embedded Algorithm

The following content will illustrate two parts. First part is to generate watermark information; the second part is the watermark embedded algorithm.

A. Generated Watermark Information

①Conduct wavelet and contourlet transform to the original image, obtain the low frequency sub-band coefficients. Sort the coefficients of the low frequency sub-band in descending order, withdraw a segment sequence of the descending order the coefficients C(s) (s=m+1,m+2,…m+n)(m+n <=the quantity of the low frequency sub-band coefficients), then remember the coordinate position of the segment sequence as key(low), when watermark need to be blind detected.

②C(s) must be transacted to W(i) (i=1,2,…n) in order to make the watermark imperceptible. Calculate the average value of the segment sequence C(s), mark it as AVER. The following is the process to get the W(i) (i=1,2,…n), which will be embedded to the original image.

If C(s)> AVER W(i)=1;

Else W(i)=-1;// (s=m+1,m+2,…m+n) (i=1,2,…n)

B. Watermark Embedded Algorithm

According to the humanity vision system (HVS) degree of illumination concealed characteristic and the texture concealed characteristic can know: The background brightness is higher, the texture is more complex, it is insensitive to human vision [7]. The variance value has reflected the block texture flat degree. When the variance is big, the block is containing a more complex texture or the edge. In order to solve contradiction in the robustness and the imperceptibility, the watermark information will be embedded to the high frequency sub-band, which has biggest value of variance among the all high frequency sub-bands.

The Watermark Embedded Algorithm is as follows:

①Conduct wavelet and contourlet transform to the original image, calculate the variance of each high frequency sub-band. Select the biggest variance of high frequency sub-bands, then sort the coefficients of the high frequency sub-band in descending order, get the coordinate position of first n big coefficients as the position of embedded watermark. The position should be remembered as key(high), when watermark need to be extracted.

②The following equation (2) is the embedded rule.

$$y_i = x_i + \kappa \times x_i \times w_i) \quad \text{(i=1,2,…,n)} \qquad (2)$$

K is embedded watermark strength. Xi (i=1,2,…n) is the selected high frequency sub-band coefficients before the embedded watermark which is the W_i (i=1,2,…n). Yi (i=1,2,…n) is the coefficients after the embedded watermark.

Ⅴ. Blind Watermark Detection Algorithm

In order to fulfill the blind watermark detection, it is the best that original image and original embedded watermark need not to be given. The following will illustrate blind watermark detection algorithm.

Barni and others [8] proposed the watermark detection method in the DFT transform domain that the original image obeys the Weibull distribution. However this method supposed that the detector knew the strength of embedded watermark when the watermark was detected, this kind of assumption is not realistic regarding the blind watermark detection. Cheng and Huang [7] proposed design method of watermark detector based on LOD (Local Optimum Detection). Essentially, the LOD was one kind of unilateral supposition detection, and the method assumes that the strength of embedded watermark only take positive. In fact, the strength of embedded watermark may possible be negative; therefore, the LOD procedure does not suit the blind watermark detection in the true sense.

From statistics viewpoint, the watermark detection is essentially the dual hypothesis. H0 represents the image does not to be embedded watermark W. H1 represents the image has been embedded watermark W.

$$H_0: y_i = x_i \qquad i = 1,2....n \tag{3}$$

$$H1: y_i = x_i + \kappa \times x_i \times w_i) \quad i = 1,2....n \tag{4}$$

In the above dual supposition detection, the high frequency sub-band coefficients of Wavelet and Contourlet transform can be regarded as noise, the embedded watermark can be regarded as signal which must be detected.

Under supposition H0, the probability density function is yi.

$$p_{y_i}(y_i, H_0) = p_x(y_i) \tag{5}$$

Under supposition H1, because the watermark is one kind of weak signal, it will not change the original coefficients the attribute, therefore |k × wi|<1. By the watermark embedded rule, may know the probability density function y_i will be the following.

$$p_{y_i}(y_i;\kappa,H_1) = \frac{1}{|1+\kappa w_i|} p_x\left(\frac{y_i}{1+\kappa w_i}\right) = \frac{1}{1+\kappa w_i} p_x\left(\frac{y_i}{1+\kappa w_i}\right) \tag{6}$$

Regarding the watermark embedded rule, the watermark detection may be represented as the following multi-sample dual supposition examination. The joint probability density function of n-D Y sample is the product of the 1-D sample probability density function, namely H1 and the H0 joint probability density respectively is the equation (7) and equation (8).

$$P_Y\left(Y;H_0\right) = \prod_{i=1}^{n} \frac{\nu}{2\mu\Gamma\left(1/\nu\right)} e^{\left(-\frac{|y_i|}{\mu}\right)^{\nu}} \tag{7}$$

$$P_Y\left(Y;\kappa,H_1\right) = \prod_{i=1}^{n} \frac{1}{1+\kappa w_i} \times \frac{\nu}{2\mu\Gamma\left(1/\nu\right)} e^{-\left(\frac{|y_i|}{\mu|1+\kappa w_i|}\right)^{\nu}} \tag{8}$$

Their logarithm likelihood ratio is equation (9).

$$l(Y) = \ln\frac{p_Y(Y;\kappa,H_1)}{p_Y(Y;H_0)} = \ln p_Y(Y;\kappa,H_1) - \ln p_Y(Y;H_0) \tag{9}$$

From the equation (7) (8), strength K is unknown. The assumption of H0 and H1 are separately corresponding to K = 0 and K ≠ 0. Because the request of watermark imperceptibility, so the strength K should be very small. $\ln P_y\left(Y;\kappa,H1\right)$ Will be carried on first-order Taylor series expansion in K=0 places, then the logarithm likelihood ratio is the equation (10).

$$\frac{\partial \ln p_Y(Y;\kappa,H_1)}{\partial \kappa}\Big|_{\kappa=0} = \sum_{i=1}^{n} \nu \left|\frac{y_i}{\mu}\right|^{\nu} w_i - \sum_{i=1}^{n} w_i \tag{10}$$

Because the W_i is the uniform distribution and each other independent between 1 and -1, so the average value is zero, namely $\sum_{i=1}^{n} w_i = 0$.

According to the definition of likelihood ratio, which should compare to the threshold value T to makes the decision. As parameter K is unknown, the dual supposition examination of equation (7) and equation (8) are bilateral supposition examination, the definition decision rule is the equation (11).

$$Decision = \sum_{i=1}^{n} \nu \left|\frac{y_i}{\mu}\right|^{\nu} w_i \underset{H_0}{\overset{H_1}{\gtrless}} \mathrm{T} \tag{11}$$

The value of μ and ν can use the maximum likelihood estimate method according to the Y, but the original image is needed. Because the W_i is the uniform distribution and each other independent between 1 and -1, the average value is zero, so Y can be replaced by Y' and the value of μ and ν can be replaced by that of μ' and ν'. The value of μ' and ν' can use the maximum likelihood estimate method according to the Y'.

μ', ν' respectively meet the equation (12) and equation (13).

$$1 + \frac{\Psi(1/\nu')}{\nu'} - \frac{\sum_{i=1}^{L} |y'_i|^{\nu'} \log|y'_i|}{\sum |y'_i|^{\nu'}} + \frac{\log(\frac{\nu'}{L}\sum_{i=1}^{L}|y'_i|^{\nu'})}{\nu'} = 0 \tag{12}$$

$$\mu' = (\frac{\nu'}{L}\sum_{i=1}^{L}|y'_i|^{\nu'})^{1/\nu'} \tag{13}$$

The equation (12) does not have the explicit solution, it may use Newton - Rapp method to iteration process [6], then can get the value of ν'. Put the value of ν' into the equation (13), and get that of μ'.

In order to fulfill the blind watermark detection, the original image is not needed. The equation (11) can be replaced by equation (14).

$$Decision = \sum_{i=1}^{n} \nu' \left|\frac{y'_i}{\mu'}\right|^{\nu} w'_i \underset{H_0}{\overset{H_1}{\gtrless}} \mathrm{T} \tag{14}$$

It is better that the original image and the original watermark information are not required when the watermark is detected. This paper can do this perfect, and fulfills the really meaning blind watermark detection algorithm, which is as following steps.

①Same as the ① and ② steps of generated watermark information, the only difference is that the image is not original image, but the image has been embedded watermark information, and the watermark information W' can be get through the key(low). W can be replaced by W'. So, when the watermark is detected, not only the original image does not request, but also the original watermark information does not request.

②Select the biggest variance of high frequency sub-band, then discover the position coefficients $Y'= \{y'_1, y'_2,\cdots, y'_n\}$ according to key(high).

③the value of the μ', ν', Y', W' can be put into the equation (14), then calculate the value of the equation (14). Next step is to calculate the value of the equation (14) of other watermark sequence groups which are not be embedded to the image, namely W_1, W_2, … W_{t-1}(t is the quantity of watermark sequence groups). All the value of equation (14) should be compare to the value of the threshold T. whichever is far greater than the threshold T, the embedded watermark can be detected. So the real blind watermark detection can be achieved.

Ⅵ. EXPERIMENTAL RESULT AND ANALYSIS

In order to evaluate the algorithm performance of above-mentioned blind watermark detection based on Generalized Gaussian Distribution. The experiment selects the original image is 512×512 Baboon image, selects the strength of watermark embedded K=0.58. Selects t=300 test watermark sequence groups (each group is 1024 - 1 or 1 uniform distribution random sequence), the 200th test group is embedded into the original image.

Due to limited space, here only gives the Figure 7, which shows the Baboon image embedded watermark suffered Histogram equalization attack. The other attacked Baboon images are omitted. The embedded watermark Baboon image is attacked by the Histogram equalization as shown Figure 7(b), which significant changed compare to the original image as is shown Figure 7(a). Because the PSNR = 20.73, the watermark algorithm is robust which can be proved by the value of the PSNR.

The details robustness experiment values of the PSNR and NC about the image of baboon are shown in the Table 1.

In the table 1, there also give the robustness experiment values of the PSNR and NC about the images of pepper (shown Figure 7(c)) and Lena (shown Figure 7(d)).

The equations of the PSNR and NC are following.

NC, the equation (15) is NC (Normalized Cross-Correlation).

In the equation (15), C(K) expresses the embedded watermark, C'(K) expresses Extracted watermark.

$$NC = \frac{\sum_{K=1}^{K} C(K) \times C'(K)}{\sqrt{\sum_{K=1}^{K} C(K)^2} \times \sqrt{\sum_{K=1}^{K} C'(K)^2}} \tag{15}$$

The equation (16) is PSNR (Peak Signal to Noise Ratio).

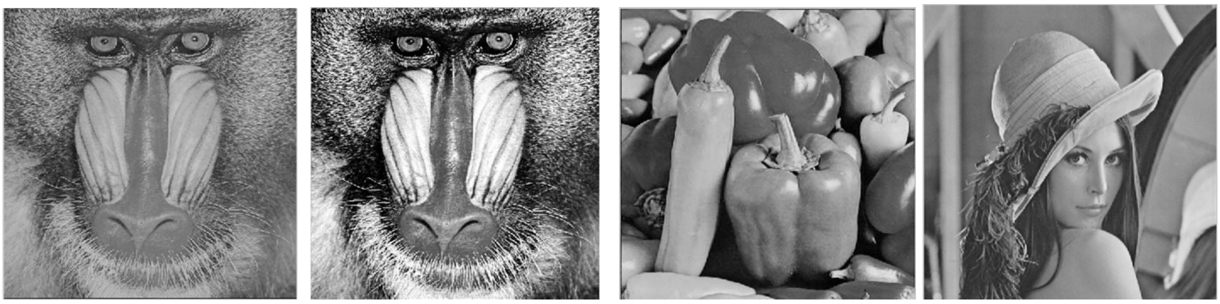
$$PSNR = MN \max_{m,n} \left(I_{m,n}^2\right) \Big/ \sum_{m,n} \left(I_{m,n} - I'_{m,n}\right)^2 \tag{16}$$

Im,n is the value of original image (m, n) Pixels, I'm,n is the value of original image that contains the watermark (m, n) Pixels.

TABLE 1 PSNR AND NC VALUE

The robust experiment (image attacked)	**Image of Baboon**				**Image of Pepper**				**Image of Lena**			
	Wavelet transform		**Contourlet transform**		**Wavelet transform**		**Contourlet transform**		**Wavelet transform**		**Contourlet transform**	
	NC	***PSNR***	***NC***	***PSNR***	***NC***	***PSNR***	***NC***	***PSNR***	***NC***	***PSNR***	***NC***	***PSNR***
0.No attack	0.99	41.65	0.97	44.77	0.99	48.93	0.96	51.91	0.99	48.10	0.96	51.05
1.JPEG compress	0.89	32.85	0.81	33.16	0.81	39.36	0.68	39.60	0.83	41.30	0.71	41.84
2.Gauss low-pass filter	0.92	36.71	0.87	37.19	0.94	44.15	0.89	44.52	0.90	45.99	0.79	46.76
3.Histogram equalization	0.64	20.73	0.53	20.73	0.65	25.71	0.56	25.72	0.70	24.12	0.60	24.12
4.Increase bright	0.71	18.13	0.64	18.13	0.73	17.90	0.65	17.90	0.65	19.07	0.53	19.07
5.Decrease dark	0.71	18.15	0.64	18.15	0.73	18.75	0.65	18.74	0.65	19.35	0.53	19.35
6.Increases contrast	0.97	35.48	0.92	36.40	0.96	35.04	0.89	35.16	0.97	36.54	0.91	36.82
7.Reduce contrast	0.71	29.39	0.64	29.39	0.73	26.44	0.65	26.44	0.65	28.74	0.53	28.73
8.Gauss noise	0.62	29.48	0.54	29.58	0.42	30.27	0.34	30.33	0.50	30.88	0.38	30.93
9.Salt &pepper noise	0.74	30.03	0.63	29.89	0.44	30.43	0.36	30.40	0.51	31.07	0.43	31.15
10.Multiplicative noise	0.67	32.62	0.66	32.91	0.56	33.65	0.48	33.74	0.67	34.54	0.57	34.30

According to the embedded watermark image is attacked by many types, May obviously see PSNR and NC are quite low from the table 1, but the watermark group can easily be detected from the figure 8 and figure 9, in other words, the performance of blind watermark detector is excellent. So the algorithm of blind watermarking detection has the actual application's value.



(a) (b) (c) (d)

Figure 7 (a) Original Image (b) Image Attacked by the Histogram Equalization (c) Image of pepper (d) Image of Lena

Figure 8 shows the result which illustrates to use blind watermark algorithm that has been described. The result is the Baboon image that is attacked by the Histogram equalization on wavelet transform domain. The other results are omitted because the limited space. Selects threshold value T=350, the value of equation (14) of 200th test group is very bigger than T, may easily detect the 200th group is the embedded watermark group.

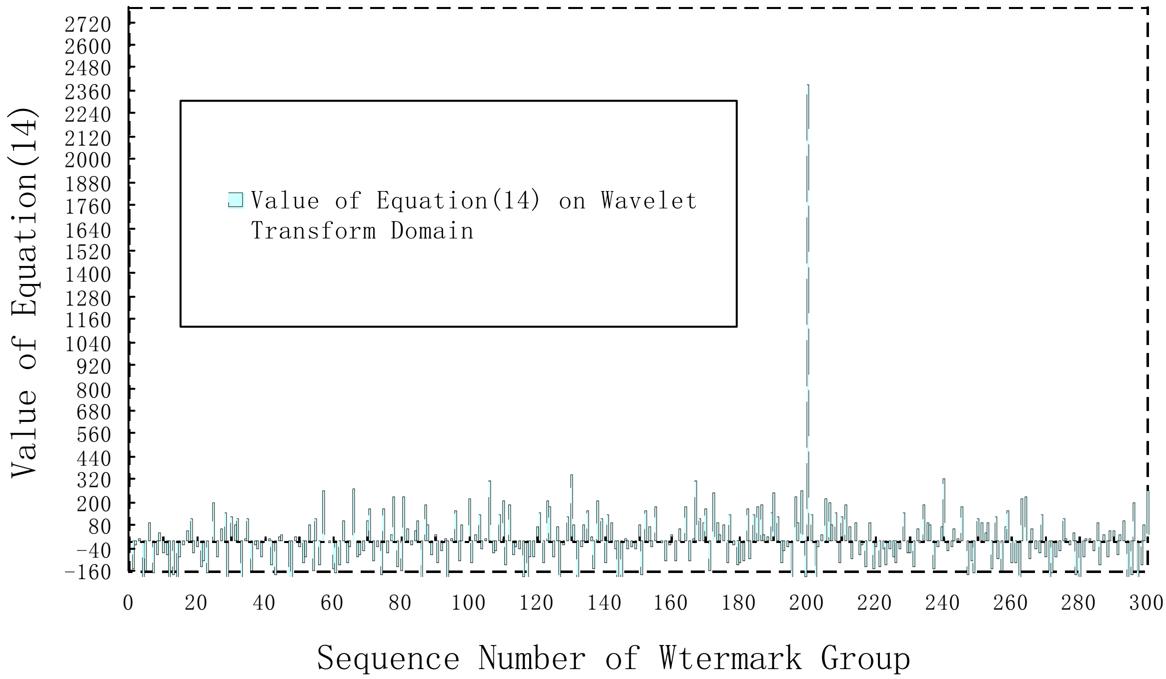


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Figure 8 Result of Blind Watermark Detection Attacked by Histogram Equalization on Wavelet

Figure 9 shows the result which illustrates to use blind watermark algorithm that has been described. The result is the Baboon image that is attacked by the Histogram equalization attack on Contourlet transform domain. The other results are omitted because the limited space. Selects threshold value T=550, the value of equation (14) of 200th test group is much bigger than T, may easily detect the 200th group is the embedded watermark group.

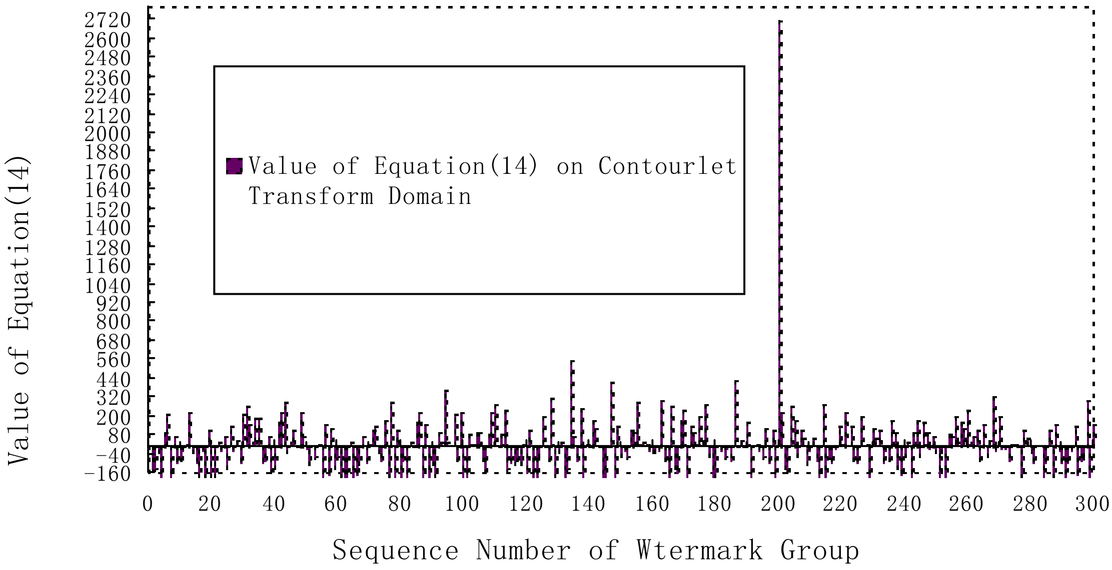

Figure 9 Result of Blind Watermark Detection Attacked by Histogram Equalization On Contourlet

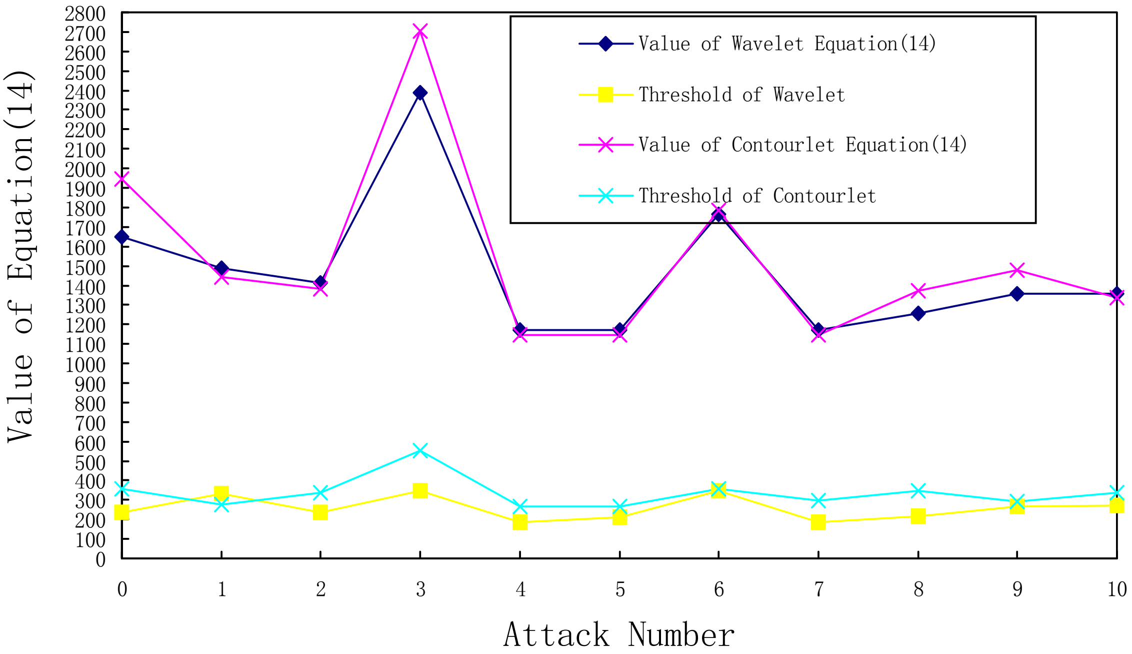

Figure 10 The Values of Equation (14) and The Values of Threshold Based on Wavelet and Contourlet Transform Domain

As shown in Figure 10, you can visually see the values of the equation (14) and threshold. These values come from variety attacks based on Wavelet and Contourlet Transform domain. X axis's values expression attack numbers, the Y axis's values expression the values of equation (14). From Figure 10, it is obvious that values of equation (14) are far bigger than that of corresponding threshold, which shows once again that the performance of blind watermark detector described in the text is wonderful.

VII. Conclusion

The high frequency sub-band coefficients of Wavelet and Contourlet transform conform to GGD (Generalized Gaussian Distribution). This article proposed the algorithm is based on GGD (Generalized Gaussian Distribution). Applying statistical inference theory, the watermark detection problem can be transformed as the dual supposition examination question. After the image embedded watermark suffers many kinds of attacks, the algorithm of blind watermark detection can very easily detect the existence of the watermark. The performance of the blind watermark detector described in the text is fine. When the watermark is detected, not only does not need the original image, but also does not need the original watermark information. The algorithm is one kind of real sense blind watermark algorithm, which has actual the application value.

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Xiang-wei Zhu He was born in October 24, 1965. He was approved as associate professor at Jiangsu Union Technical Institute in 2005. He received his Master Degree in the Institute of Computer Science, Nanjing university of Science and Technology in January 2008.

His research interest covers image compression, the theories of wavelet transform and contourlet transform, as well as their applications on watermarking fields.

His paper of "Research of Multiple Watermarks Algorithm in E-commerce Copyright Protection and Tracking" Proceedings of the 2008 International Conference on Computational Intelligence and Security (CIS-2008) was awarded the best paper by IEEE.