A semi-fragile lossless digital watermarking based on adaptive threshold for image authentication

Zhenyong Chen

School of Computer Science and Engineering, Beihang University, Beijing, 100191, China and Research Institute of Beihang in Shenzhen, Shenzhen, 518000, China E-mail: chzhyong@buaa.edu.cn

Fangjie Fu, Zhuo Wang*, Wei Fan and Zhang Xiong

School of Computer Science and Engineering, Beihang University, Beijing, 100191, China E-mail: ffj@cse.buaa.edu.cn E-mail: superwz@cse.buaa.edu.cn E-mail: fanwei@buaa.edu.cn E-mail: xiongz@buaa.edu.cn *Corresponding author

Abstract: In this paper, a novel semi-fragile lossless digital watermarking method based on adaptive threshold for image authentication is presented. Most of the existing semi-fragile lossless watermarking schemes are based on modulo-256 addition to achieve losslessness. In order to avoid the salt-and-pepper noise, some of the schemes ignore the blocks which lead to overflow/underflow, and using error correction codes (ECCs). But the ECC will reduce available embedding capacity, especially for the complex images. We then propose an adaptive threshold method to improve the existing schemes. By employing a robust statistical quantity based on the patchwork to embed data, identifying image complexity based on wavelet-domain generalised Gaussian distribution (GGD) and using it to adaptively quantise thresholds which differentiating the embedding process, and using simple ECC, this technique has achieved losslessness, robustness and more competitive available embedding capacity. Experimental results demonstrate that the capacity of watermarked image of this technique is highly improved, and the quality of the image is acceptable.

Keywords: digital watermark; lossless data hiding; semi-fragile watermark; adaptive threshold; robustness.

Reference to this paper should be made as follows: Chen, Z., Fu, F., Wang, Z., Fan, W. and Xiong, Z. (2013) 'A semi-fragile lossless digital watermarking based on adaptive threshold for image authentication', *Int. J. Multimedia Intelligence and Security*, Vol. 3, No. 1, pp.63–79.

Biographical notes: Zhenyong Chen received his Bachelor, Master and Doctoral degrees from Tsinghua University, Beijing, China. He is currently an Associate Professor in the School of Computer Science and Engineering, in Beihang University, Beijing, China. His research interest includes information hiding, digital watermarking, digital rights management and video encryption.

Fangjie Fu is currently pursuing his Bachelor in Computer Science and Engineering from Beihang University, Beijing, China. His research interest includes digital watermarking, digital rights management and multimedia processing.

Zhuo Wang is currently pursuing his Bachelor in Computer Science and Engineering from Beihang University, Beijing, China. His research interest includes digital watermarking, digital rights management and multimedia processing.

Wei Fan is currently pursuing her PhD in Computer Science and Engineering from Beihang University, Beijing, China. Her research interest includes digital watermarking, digital rights management and multimedia processing.

Zhang Xiong received his Bachelor degree in Harbin Engineering University, Harbin, China; and received his Master degree in Beihang University, Beijing, China, in 1984. He is currently a Professor and PhD Supervisor in Computer Science and Engineering in Beihang University. His research interests include multimedia, computer control and information system.

1 Introduction

Digital watermarking technique is a process to embed watermark data into digital media such as audio files, video streams or images, and most of these changes are not perceptible. It can be used as a way to transport secret information for the purposes of authentication and security, or to protect the integrality of the original media such as copyright protection (Zou et al., 2003).

In this paper, we mainly focus on image data hiding. Many image data hiding algorithms have been proposed in recent years. Most of the algorithms are irreversible, because the stego-image suffer permanent distortion when embedding process. However, in some fields such as military images, law enforcement and medical images, the original images are important and it is desired to recover the original ones without any distortion after the hiding data are extracted. Recently many lossless or invertible watermarking techniques which satisfying these circumstances have been proposed, such as those reported in Fridrich et al. (2001), Xuan et al. (2002), De Vleeschouwer et al. (2003), Shi et al. (2004), Zou et al. (2006), Maeno et al. (2006), Ni et al. (2008), Zhao et al. (2010), Zhao and Yang (2011) and Chen et al. (2010). The above mentioned methods can reverse the marked image back to the original image with no distortion. But most of them are fragile watermarking that the hiding data can not be extracted correctly after image compression or other incidental image processing which is not malicious modifications. This kind of lossless watermarking is called fragile watermarking that is proposed to detect malicious modifications. However, in some applications, it too strict to forbid

A semi-fragile lossless digital

compression. Thus, the lossless semi-fragile data hiding algorithms are proposed (De Vleeschouwer et al., 2003; Ni et al., 2008; Ni et al., 2006).

Figure 1 Examples of salt-and-pepper: (a) computed tomography (De Vleeschouwer et al., 2003) (b) woman (see online version for colours)



(a)



(b)

De Vleeschouwer et al.'s (2003) algorithm is a semi-fragile lossless watermarking against JPEG compression. It use modulo-256 addition and can be applied to image authentication. However, in this method, there is a big weakness that some marked image suffer from salt-and-pepper noise caused by using modulo-256 addition to prevent overflow/underflow. Figure 1 is two examples.

For avoiding overflow/undoerflow problem, Ni et al.'s (2008) propose a robust lossless image data hiding method based on pixel group's distribution characteristics, using error correction codes (ECCs) and permutation scheme. Below is a brief overview of the algorithm.

1 First, each bit of the watermark data is embedded into a block which can be a regular size (8×8 , 16×16 , etc.) in an image. Each block is split into two sets of pixels as shown in Figure 2 (Ni et al., 2008). Consider an 8×8 block, set A is denoted by a_i , the set B b_i , we choose a pixel pair as two horizontally neighbours (one is in set A, the other is in set B). Formula (1) is the equation to calculate the difference value between set A and set B.

$$\gamma = \frac{1}{n} \sum_{i=1}^{n} (a_i - b_i) \quad \text{where } n \text{ is the number of the pairs.}$$
(1)

As the local similarity of pixels, γ is expected to be close to zero. It can be shifted to embed a bit of hiding data into one block.

- 2 One bit is embedded in each block. If the bit is '0', the γ is kept within thresholds *K* and -K (less than 5 in Ni et al., 2008). On the other hand, the bit is '1', the γ is shifted beyond the thresholds *K* or -K. For avoiding the overflow/underflow, the blocks is classified into four categories, and use different way to bit-embedding in different category.
- 3 In some kind of categories, there may be some error bits caused by bit-embedding process. So ECC is be used to correct error bits.

Figure 2	Sets A	marked by	'+', sets	В	marked	by	'
----------	--------	-----------	-----------	---	--------	----	---

+	_	+	_	+	_	+	_
	+		+	l	+		+
+	_	+	_	+	_	+	_
	+		+	I	+		+
+	_	+	_	+	_	+	_
	+	I	+	I	+		+
+	_	+	_	+	_	+	_
_	+	_	+	_	+	_	+

Apparently, the difference value γ depends on the pixel greyscale values in sets A and B. From the local similarity, this method can defend against JPEG compression. However, in order to correct error bits, ECC is used at the price of reduce available data embedding capacity. Especially for the complex images, more powerful ECC is needed which means more redundant bits and less available embedding capacity. In Section 2, we propose an adaptive threshold method to improve the available data embedding capacity. By identifying image complexity based on wavelet-domain generalised Gaussian distribution (GGD), we adaptively set thresholds *K* for each block to reduce the probability that the block is belong to the categories in which the bit-embedding process will introduce error bits, so less powerful ECC can meet the need, the data embedding capacity is improved. In Section 2.4.1, we will discuss the error in classification of data extraction which is not mentioned in Ni et al. (2008). From the experimental results, our method can improve the data embedding capacity at the price of sacrificing a little image quality.

2 A novel semi-fragile lossless digital watermarking based on adaptive threshold

In order to adaptively embedding hiding data into cover image, we select an adaptive parameter to set thresholds *K*. In this proposed method, the following image complexity is selected as the parameter.

2.1 A image complexity used for adaptively embedding hiding data

As a common statistical model of image, image complexity is described by several papers (Huang and Mumford, 1999; Wainwright and Simoncelli, 2000; Srivastava et al., 2003; Liu et al., 2008), such as the GGD, the Gaussian mixture model (GMM), and Markov random field (MRF) models. We use GGD to describe the statistical model. Density function of GGD is the extension of generalised gamma distribution's density function. Mathematical function is equation (2).

$$f(x;\alpha,\beta,\mu) = \left[\frac{\alpha}{2\beta\Gamma(1/\alpha)}\right] e^{\left[-\frac{|x-\mu|^{\alpha}}{\beta}\right]^{\alpha}}$$
(2)

where

$$\beta = \sqrt{\frac{\sigma^2 \Gamma(1/\alpha)}{\Gamma(3/\alpha)}}, \sigma > 0$$

with $\Gamma(:)$ is gamma distribution function.

$$\Gamma(z) = \int_{0}^{\infty} e^{-t} t^{z-1} dt$$

2.1.1 An estimation of image complexity

In equation (2), α is the shape parameter which is inversely proportional to the decreasing rate of the peak. We use it as image complexity. In Liu et al. (2008), a curve-fitting method is proposed to calculate α as follows.

For GGD, generally consider the case mean value $u = 0, x = (x_1, x_2, ..., x_n)$ is a sample of GGD. As first-order origin moment of GGD is zero, absolute moment can be used to calculate α .

When u = 0, the first order absolute moment is proposed as

$$m_{1} = E\{|x|\}$$

$$= \int_{-\infty}^{+\infty} |x| \frac{\alpha}{2\beta\Gamma(1/\alpha)} e^{-\frac{|x|^{\alpha}}{\beta}} dx$$

$$= \frac{\alpha}{\beta\Gamma(1/\alpha)} \int_{0}^{+\infty} |x| e^{-\frac{|x|^{\alpha}}{\beta}} dx$$
(3)

With $-\left|\frac{x}{\beta}\right|^{\alpha} = y$, we have $x = \beta y^{1/\alpha}$, $dx = \frac{\beta}{\alpha} y^{\frac{1}{\alpha}-1} dy = 2$. It together with equation (3) implies

$$\frac{\alpha}{\beta\Gamma(1/\alpha)} \int_{0}^{+\infty} y^{\frac{2}{\alpha}-1} e^{-y} dy = \beta \frac{\Gamma(2/\alpha)}{\Gamma(1/\alpha)}$$
(4)

Let $\beta = \sqrt{\frac{\sigma^2 \Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$, equation (4) implies

$$m_1 = E\{|x|\} = \sigma\beta \frac{\Gamma(2/\alpha)}{\sqrt{\Gamma(1/\alpha)\Gamma(3/\alpha)}}$$
(5)

Similarly computer the second-order moment as

$$m_2 = E\left\{ \left| x^2 \right| \right\} = \sigma^2 \tag{6}$$

With
$$E\{|x|\} = \frac{\alpha^2 \Gamma^2(2/\alpha)}{\Gamma(1/\alpha)\Gamma(3/\alpha)}$$
, let

$$R(\alpha) = \frac{E^2\{|X|\}}{E\{X^2\}} = \frac{\Gamma^2(2/\alpha)}{\sqrt{\Gamma(1/\alpha)\Gamma(3/\alpha)}} = \frac{m_1^2}{m_2}$$
(7)

 $R(\alpha)$ is called GDD parameters ratio function. The estimated values (\hat{m}_1, \hat{m}_2) of m_1, m_2 is calculated as follows:

$$\hat{m}_1 = \frac{1}{n} \sum_{i=1}^n |x_i|, \ \hat{m}_2 = \frac{1}{n} \sum_{i=1}^n x_i^2$$
(8)

With equations (7) and (8), the estimated value of α is implied

$$\hat{\alpha} = R^{-1} \left(\frac{\hat{m}_1^2}{\hat{m}_2} \right) \tag{9}$$

A semi-fragile lossless digital

With a hyperbolic function fitting the original function $R(\alpha)$, Fitting model is y = a + b / x. We use least squares fitting to compute approximating function

$$y = 0.77127 - \frac{0.26961}{x} \tag{10}$$

So

$$R^{-1}(x) = \frac{-0.26961}{x - 0.77127} \tag{11}$$

With equations (9) and (11), the estimated value of α can be calculated.



Figure 3 Test images of the image complexity, (a) Lena (b) plane (c) baboon (d) salboat

2.1.2 Analysis of the results

In order to verify that the image complexity is effective, we test for the images in Figure 3. Result is shown in Table 1. The table indicates that the image with low complexity has low α and the image with high complexity has high α .

Images	Parameter α
Lena	0.5981
Baboon	0.791
Plane	0.4987
Sailboat	1.0132

 Table 1
 Image complexity of test images

2.2 Bit-embedding process based on adaptive threshold

In Ni et al. (2008), the bit-embedding process is that one bit is embedded in each block, the difference value γ is kept within thresholds K and -K (less than 5 in Ni et al., 2008) to embed '0' and the γ is shifted beyond the thresholds K or -K to embed '1'. For avoiding the overflow/underflow, the blocks is classified into four categories, and there are several different cases in each category. Different way is used to bit-embedding in different case of category. In some kind cases of categories, there may be some error bits caused by bit-embedding process. So ECC is be used to correct error bits. We propose a new method that an adaptive thresholds K is set based on image complexity for each block to reduce the number of the cases of categories and the probability that the block is belong to the cases of categories in which the bit-embedding process will introduce error bits, so less powerful ECC can meet the need, the data embedding capacity is improved.

From a large number of experiments, we define the adaptive relationship between the threshold *K* and image complexity α [refer to equation (12)] and experimental results are best.

	2	0	\leq	$ \alpha $	<	0.4	
	3	0.4	\leq	$ \alpha $	<	0.7	
	6	0.7	\leq	$ \alpha $	<	1.4	
K = <	9	1.4	\leq	$ \alpha $	<	2.1	(12
	12	2.1	\leq	$ \alpha $	<	2.8	
	15	2.8	\leq	$ \alpha $	<	5	
	18	5	\leq	$ \alpha $			

2.2.1 Details of bit-embedding process

Below are the details of the bit-embedding process. The diagram of the block classification in this paper is shown in Figure 4. We also classify the blocks into four categories. For the adaptive threshold makes the probability that $|\gamma|$ is beyond the threshold *K* is very lower than in Ni et al. (2008), the error bits introduced by bit-embedding is fewer. In the case $|\gamma| \ge K$, if it do not lead to overflow/underflow, we shift γ , else we do not change the values of the block. The possibly introduced error will

be corrected by using ECC. In this paper, the shift value θ equal twice of the adaptive threshold *K*. Shift γ towards right/left side means adding/subtracting a shift value θ to the value of each pixel in set A, and the pixel in set B is never changed. The flow diagram of the bit-embedding process is shown in Figure 6.

Figure 4 Bit embedding in different category



2.2.1.1 Category 1

Pixel values are in the central part of histogram. It is means that the distance $d(equals \min(d_{right}, d_{left}))$ is beyond θ as show in Figure 5.

According to the value γ , there are two cases:

- Case $|\gamma| \le K$: If embedding 1, shift γ by θ to left or right side depending on that is negative or positive, else the pixel values are not changed.
- Case | *γ*| > *K*: In order to keep the reversibility of this algorithm, whether embedding 1 or 0, we shift the *γ* to embedding 1.

2.2.1.2 Category 2

Pixel values are in the left side of histogram. It is means that $d_{left} < \theta$. According to the value, there are two cases:

- Case $|\gamma| \le K$: If embedding 1, shift γ by θ to right side else the pixel value is not changed.
- Case |γ| > K: In order to keep the reversibility of this algorithm, whether embedding 1 or 0, if γ > K, we shift the γ by θ to right side, else the pixel values are intact. The error bit will be corrected by ECC.

2.2.1.3 Category 3

Pixel values are in the right side of histogram. It is means that $d_{right} < \theta$. In this category, it is similar to the Category 2 except shifting the γ by θ to left side instead of to right side.

2.2.1.4 Category 4

Pixel values are in the both sides of histogram. No matter what is embedded, the pixel value remains unchanged.

2.3 ECC and permutation of hiding data

Because some error bit may be introduced in all case 2 of the categories and Category 4, ECC is necessary to correct the mistakes. In the proposed algorithm, for the adaptive threshold reduce the probability of the embedding mistakes, the less powerful code can meet the experimental requirement such as BCH(15, 11, 1), BCH(15, 7, 2) or BCH(15, 5, 3).

In order to strengthen security of the hiding data, the bit stream is permuted by a pseudo-random sequence using a secret key, and the key is transmitted through other secure data channel. The other benefit of permutation is that the changed pixels of the image are distributed more uniformly, and human eyes are difficult to detect the change.

A semi-fragile lossless digital

Figure 7 Flow diagram of data extraction

2.4 Data extraction

At the receiver side, the process of the data extraction is the inverse process of data embedding. We get the key and the marked image, divide image into blocks and calculate the embedded bit in each block. Finally, the bit stream is inversely permutated and decoded to get the hiding data. The flow diagram of data extraction is shown in Figure 7.

2.4.1 Error in classification

In Ni et al. (2008), the error bits introduced in embedding process are discussed and ECC is used to correct the error bits, however, the error in classification of data extraction which may be corrected by ECC is ignored. For example, a block belong to the case 1 of Category 1, but its d_{left} is near to the θ . After shifting toward left-hand side, it may not belong to the Category 1 as shown in Figure 8, and it will introduce new errors when extraction. In order to reduce the classification errors in extraction, the set A and B are separately classified, and consider both of them to classify the block in extraction as follows:

$$Category_{block} = \begin{cases} category_{setA} & \text{if setA} = \text{setB or setA} = \text{Category}_{1} \\ category_{setB} & \text{or setB} = \text{Category}_{2} \\ category_{setB} & \text{else condition} \end{cases}$$

3 Experimental results

We use 39 greyscale images to test our proposed algorithm, and watermark embedded into them is shown in Figure 9. Because of using lower powerful ECC, our algorithm has bigger embedding capacity than in Ni et al. (2008), and the quality of images is acceptable. The original image, watermarked image and watermarked image using method in Ni et al. (2008) are shown in Figure 10.

Figure 9 Watermark is embedded

Figure 10 Test results of an image in two method, (a) original image (b) watermarked image (c) watermarked image using method in Ni et al. (2008) the number of error bits 39 images result our method in Ni et al. (2008)

(b)

In order to prove that our method reduces the probability of the error bits, we do not use ECC to correct the error bits in comparison test. Comparison test result is shown in Figure 11, it is note that the average error bits of our algorithm is fewer than (Ni et al., 2008), especially for the complex images.

Because our algorithm is an improvement of Ni et al. (2008), it inherits the resistance of JEPEG/JEPEG2000 compression. In another word, the watermark can be extracted without error after common image compression. From the experimental results shown in Table 2, our method has robustness against image compression, and can improve the data embedding capacity at the price of sacrificing a little image quality. Especially for the complex images such as baboon, we use BCH(31, 6, 7) instead of BCH(63, 7, 15), and the experimental results shown in Table 3.

Table 2Comparison of PSNR

	PSNR(dB) of our method	Robustness (bpp)	PSNR(dB) of Ni et al. (2008)
Lena	37.9	0.8	40.2
Baboon	34.1	1.6	38.7
Boat	37.3	1.0	40.5
Camera	31.5	1.2	34.6
Average of 39 images	34.2	1.1	37.6

Table 3Comparison of PSNR

Image	Size	Payload (bits)	Available embedding capacity (ACE) of our method	ACE of Ni et al. (2008)
Lena	512 × 512	4,096	792	1,365
Baboon	512 × 512	4,096	585	792
Boat	512 × 512	4,096	560	792
Camera	512 × 512	4,096	585	792
Average of 39 images	512 × 512	4,096	634	923

4 Conclusions

This paper discussed a novel semi-fragile lossless watermarking technique which can resist common image compression, have competitive embedding capacity and acceptable quality of the output image. The embedded watermark can include authentication information which can identify the malicious attacks. We propose an adaptive threshold method to improve the available data embedding capacity. By identifying image complexity based on GGD, we adaptively set thresholds to each block to embed data bits. This proposed method also has flexibility. Based on our experience, we can limit the thresholds between two to five to improve quality of the image while having the same embedding capacity of Ni et al. (2008). Our future directions include: improving quality of the marked image, extending our algorithm to transform domain such as DWT and DCT, reducing the number of error bits introduced in bit-embedding process.

Acknowledgements

This work is supported by the Fundamental Research Funds for the Central Universities, National High Technology Research and Development Programme (863 Programme) of China (2011AA010502), PhD Programmes Foundation of Ministry of Education of China (20091102110017) and Shenzhen Key Laboratory of Data Vitalisation (Smart City).

References

- Chen, Z., Fan, W., Xiong, Z., Zhang, P. and Luo, L. (2010) 'Visual data security and management for smart cities', *Frontiers of Computer Science in China*, Vol. 4, No. 3, pp.386–393.
- De Vleeschouwer, C., Delaigle, J.F. and Macq, B. (2003) 'Circular interpretation of bijective transformations in lossless watermarking for media asset management', *Multimedia, IEEE Transactions on*, Vol. 5, No. 1, pp.97–105.
- Fridrich, J., Goljan, M. and Du, R. (2001) 'Invertible authentication watermark for jpeg images', in Information Technology: Coding and Computing, Proceedings. International Conference on, pp.223–227, IEEE.
- Huang, J. and Mumford, D. (1999) 'Statistics of natural images and models', in *Computer Vision* and Pattern Recognition, IEEE Computer Society Conference on, Vol. 1, IEEE.
- Liu, Q., Sung, A.H., Ribeiro, B., Wei, M., Chen, Z. and Xu, J. (2008) 'Image complexity and feature mining for steganalysis of least significant bit matching steganography', *Information Sciences*, Vol. 178, No. 1, pp.21–36.
- Maeno, K., Sun, Q., Chang, S.F. and Suto, M. (2006) 'New semi-fragile image authentication watermarking techniques using random bias and nonuniform quantization', *Multimedia, IEEE Transactions on*, Vol. 8, No. 1, pp.32–45.
- Ni, Z., Shi, Y.Q., Ansari, N. and Su, W. (2006) 'Reversible data hiding', *Circuits and Systems for Video Technology, IEEE Transactions on*, Vol. 16, No. 3, pp.354–362.
- Ni, Z., Shi, Y.Q., Ansari, N., Su, W., Sun, Q. and Lin., X. (2008) 'Robust lossless image data hiding designed for semi-fragile image authentication', *Circuits and Systems for Video Technology, IEEE Transactions on*, Vol. 18, No. 4, pp.497–509.
- Shi, Y.Q., Ni, Z., Zou, D., Liang, C. and Xuan, G. (2004) 'Lossless data hiding: fundamentals, algorithms and applications', in *Circuits and Systems, ISCAS '04, Proceedings of the 2004 International Symposium on*, Vol. 2, pp.II–33, IEEE.

- Srivastava, A., Lee, A.B., Simoncelli, E.P. and Zhu, S.C. (2003) 'On advances in statistical modeling of natural images', *Journal of Mathematical Imaging and Vision*, Vol. 18, No. 1, pp.17–33.
- Wainwright, M.J. and Simoncelli, E.P. (2000) 'Scale mixtures of Gaussians and the statistics of natural images', Advances in Neural Information Processing Systems, Vol. 12, No. 1, pp.855–861.
- Xuan, G., Zhu, J., Chen, J., Shi, Y.Q., Ni, Z. and Su, W. (2002) 'Distortionless data hiding based on integer wavelet transform', *Electronics Letters*, Vol. 38, No. 25, pp.1646–1648.
- Zhao, J. and Yang, F. (2011) 'A semi-fragile digital watermark for image content authentication', *Computer*, p.1.
- Zhao, X., Ho, A.T.S. and Shi, Y.Q. (2010) 'Image forensics using generalised Benford's law for improving image authentication detection rates in semi-fragile watermarking', *International Journal of Digital Crime and Forensics (IJDCF)*, Vol. 2, No. 2, pp.1–20.
- Zou, D., Shi, Y.Q., Ni, Z. and Su, W. (2006) 'A semi-fragile lossless digital watermarking scheme based on integer wavelet transform', *Circuits and Systems for Video Technology, IEEE Transactions on*, Vol. 16, No. 10, pp.1294–1300.
- Zou, D., Xuan, G. and Shi, Y.Q. (2003) 'A content-based image authentication system with lossless data hiding', in *ICME*, pp.213–216, IEEE.