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Novel Fragile Watermarking Scheme using an Artificial Neural Network for Image Authentication

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Abstract: This paper presents a novel fragile watermarking scheme based on an artificial neural network (ANN). The fragile watermark is designed according to the characteristics of the original image. If the image is modified, the alteration can be detected via the fragile watermark without original image. Based on the type of alteration, we can determine what modifications have been performed. An artificial neural network is used to analyze the modifications. The experimental results show that the proposed method can detect tampering, locate where the tampering has occurred, and recognize what kind of alteration has occurred. This method has a high success ratio in recognizing the types of modifications and provides sufficient evidence. The experimental results demonstrate that our method is indeed effective.

Keywords: artificial neural network, discrete wavelet transform (DWT), fragile watermarking, image authentication, watermarking.

1 Introduction

A fragile watermark is useful in image authentication applications [1, 4-6, 11, 14-23]. It can detect slight changes in the image and prevent mark-transfer attacks (replacing or covering the owner's watermark with that of the attacker)[2]. In the past, most fragile watermark systems worked by inserting watermark data or modifying some coefficients directly in the host image [3, 8, 9, 10, 12]. Indeed, it does make sense to embed some data into the image as a robust watermark that carries proof of authorship. However, there are problems with these systems. These methods need original images when they extracted the fragile watermarks. At the same time, they cannot encode the features of the image, nor can they be used to identify what kind of modification has occurred. As a result, these methods can allow the detection of only certain kinds of distortion. In addition, these fragile watermarking methods sometimes destroy the host image. In order to overcome these problems, we here propose a novel artificial neural network-based fragile watermarking scheme, as shown in Fig. 1. The fragile watermark is designed according to the wavelet coefficients of the host image. This fragile watermark can record the characteristics of the original image and be extracted without original image. After the fragile watermark is extracted, the approximate host image can be reconstructed. Then a modified image can be detected according to the fragile watermark and the reconstructed image. Afterward, an artificial neural network is used to analyze the tampering of the host image, locate where the tampering has occurred, and identify what kind of alteration has occurred. The fragile watermark provides sufficient authentication evidence. This method is novel and efficient.

The paper is organized as follows. The fragile watermarking procedures are described in Section 2. Section 3 describes the artificial neural network model. The experimental results and discussions are presented in Section 4. In Section 5, the conclusion of this paper is stated.

2 Fragile Watermarking Procedures

We propose a novel fragile watermarking scheme in this paper. In our approach, a DWT-based algorithm is developed to embed the fragile watermark.

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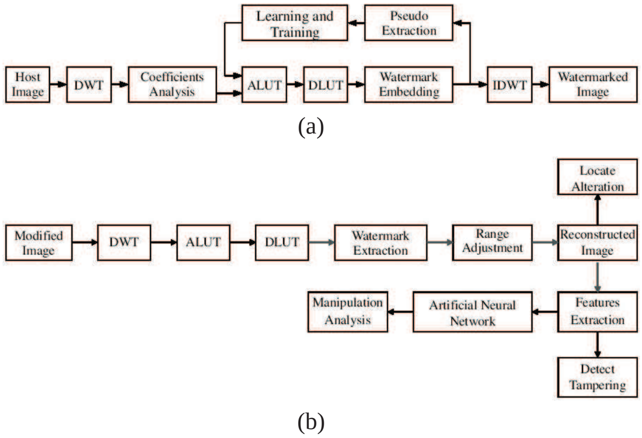


Fig. 1: Artificial neural network-based fragile watermarking. (a) Fragile watermark embedding (b) Fragile watermark extraction and analysis.

2.1 Fragile Watermark Embedding.

First, the host image is transformed by the discrete wavelettransform (DWT) to transfer the image information from the spatialdomain to the wavelet domain. We analyze the coefficients in the high-high band (HH_p, $p = 1,2,3\cdots$) after the DWT. We analyze the average value, difference value, and wavelet coefficient magnitude.

After the DWT, we calculate the average value M_{mn} for each of the 2x2 wavelet coefficients (Fig. 2(a) and Fig. 2(b)). Then an approximate look-up table (ALUT) is generated to encode the average value M_{mn} (Table 1). The ALUT is designed according to the distribution of the coefficients value. Based on the ALUT, M_{mn} is transformed into binary data. Then the binary data are permuted in order (Fig. 2(c)). We use this binary data as fragile watermark F_1, which is embedded into the $HH_p(p = 1,2,\cdots)$ band, and on which the exclusive-or (XOR) operation and the least significant bit (LSB) of wavelet coefficients are performed to obtain embedding data. The embedding data are embedded into the $HH_p(p = 1,2,3\cdots)$ band (Fig. 2(d)). The coefficients in the high frequency range stand for high resolution and represent a subtle difference in the image. If the host image is modified, any slight changes can be detected. As fragile watermark F_1 is designed according to the characteristics of the image, we can reconstruct the original features of the image even after the image is modified.

In order to increase the resolution of fragile watermark F_1, we consider the error due to the ALUT processing. After DWT, we also calculate the maximum difference value for each of the 2x2 wavelet coefficients D_{mn} (Fig.3(a) and Fig. 3(b)). Then a difference look-up

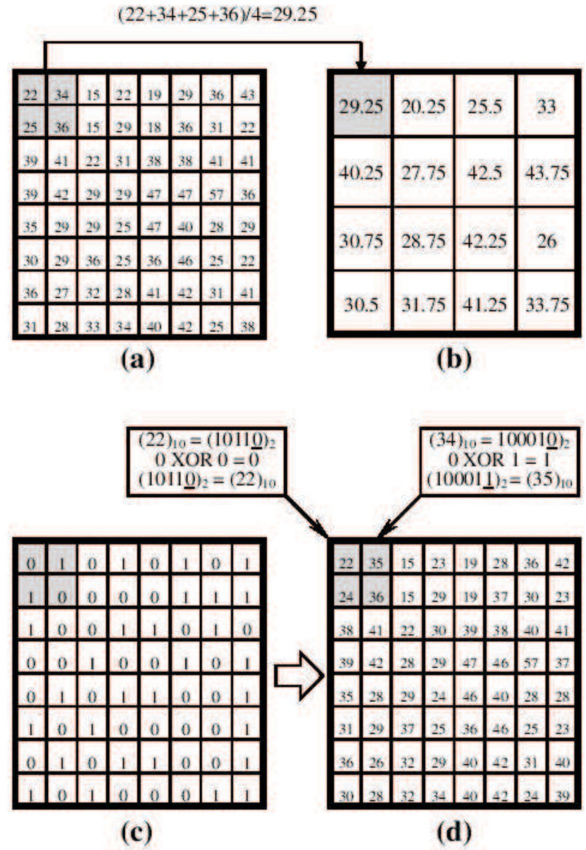


Fig. 2: Embedding the fragile watermark F_1 into the HH_1 band. (a) Wavelet coefficients (HH_1). (b) The average value M_{ij} for each of the 2x2 wavelet coefficients. (c) Fragile watermark F_1. (d) Embedding the fragile watermark F_1 into the HH_1 band.

table (DLUT) is generated to encode the difference values D_{mn} (Table 2). The DLUT is designed according to the distribution of the coefficients value. Based on the DLUT, D_{mn}'s are transformed into binary data. Then the binary data are permuted in order. We use this binary data as another fragile watermark, F_2 (Fig. 3(c)). F_2 is embedded into the $HL_p(p = 1,2,3\cdots)$ band, and then we perform the exclusive-or (XOR) operation on this watermark and the least significant bit LSB of wavelet coefficients ($HL_p(p = 1,2,3\cdots)$ band) to the obtain the embedding data. The embedding data are embedded into the $HL_p(p = 1,2,3\cdots)$ band (Fig. 3(d)). The coefficients in the high frequency range stand for high resolution and can represent subtle differences in the image. When the host image is modified, any slight changes can be detected. When the image is reconstructed, we can eliminate the error in the approximate image using F_2.

In order to increase the resolution of the fragile watermark, we consider the error during the ALUT processing. Let V_{mn} be the F_3 value obtained by

Table 1: Approximate Look-Up Table (ALUT).

Range	0~2.5	2.5~7.5	7.5~12.5	12.5~17.5	17.5~22.5	22.5~27.5
Approx. Value	0	5	10	15	20	25
Code	0000	0001	0010	0011	0100	0101
Range	27.5~32.5	32.5~37.5	37.5~42.5	42.5~47.5	47.5~52.5	52.5~57.5
Approx. Value	30	35	40	45	50	55
Code	0110	0111	1000	1001	1010	1011

Table 2: Difference Look-Up Table (DLUT).

Range	0~2.5	2.5~7.5	7.5~12.5	12.5~17.5	17.5~22.5	22.5~27.5
Difference Value	0	5	10	15	20	25
Code	0000	0001	0010	0011	0100	0101
Range	27.5~32.5	32.5~37.5	37.5~42.5	42.5~47.5	47.5~52.5	52.5~57.5
Difference Value	30	35	40	45	50	55
Code	0110	0111	1000	1001	1010	1011

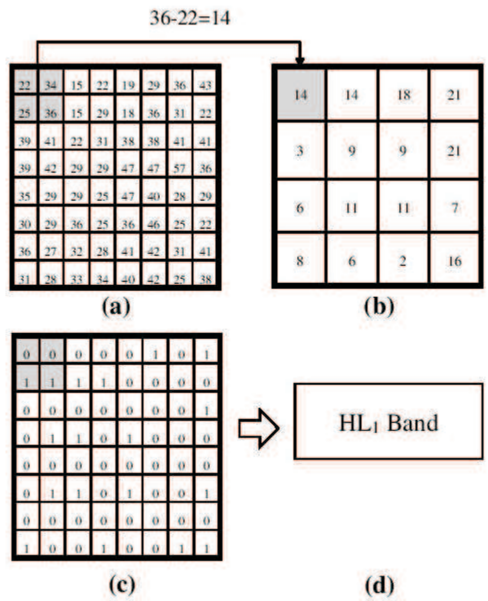


Fig. 3: Embedding the fragile watermark F_2 into the HL_1 band. (a) Wavelet coefficients (HH_1). (b) The difference value for each of the 2x2 wavelet coefficients D_{ij}. (c) Fragile watermark F_2. (d) Embedding the fragile watermark F_2 into the HL_1 band.

comparing the wavelet coefficient with the average value (Fig. 4(a) and Fig. 4(b)) as follows:

$$V_{mn} = 1 \quad \text{if wavelet coefficient} > \text{average value}$$
$$V_{mn} = 0 \quad \text{if wavelet coefficient} < \text{average value}$$

We use this binary data as another fragile watermark, F_3 (Fig. 4(c)). F_3 is embedded into the $LH_p(p = 1,2,3\cdots)$ band. We perform the exclusive-or (XOR) operation on fragile watermark F_3 and the least significant bit (LSB) of wavelet coefficients ($LH_p(p = 1,2,3\cdots)$ band) to obtain the embedding data. The coefficients in the high frequency range stand for high resolution and represent a subtle difference in the image. When the host image is modified, any slight changes can be detected. When the image is reconstructed, we can revise the error in the approximate image using F_3.

In order to increase the quality of the fragile watermarks, a pseudo extraction function extracts the fragile watermarks (F_1, F_2, F_3). Then the adaptive learning and training function analyze the embedding quality and modify the ALUT and DLUT repeatedly to obtain the optimization tables (Fig. 1).

2.2 Fragile Watermark Extraction and Analysis.

First, we transform the modified image using DWT and extract the fragile watermark F_{M1} in the $HH_p(p = 1,2,3\cdots)$ band, F_{M2} in the $HL_p(p = 1,2,3\cdots)$ band, and F_{M3} in the $LH_p(p = 1,2,3\cdots)$ band. Comparing the extracted fragile watermarks (F_{M1}, F_{M2}, F_{M3}) with the fragile watermarks (F_1, F_2, F_3), we can find the differences between the host and the modified images (Fig.5). Because the wavelet coefficients stand for the spatial characteristics of the host image, we can locate where the tampering has occurred. After comparing the fragile watermarks (F_1, F_2, F_3) with the modified fragile watermarks (F_{M1}, F_{M2}, F_{M3}), we can extract the difference features, DF_1. Any slight modification can be detected easily from analysis of the variations in the fragile watermark (Fig. 5).

Then we use the fragile watermarks (F_1, F_2, F_3) to reconstruct the approximate host image I_R (Fig. 6). We also use the extracted fragile watermarks (F_1, F_2, F_3) to reconstruct the modified image I_M. Comparing the approximate host image I_R and modified image I_M, we can find the differences between the approximate host image and modified image. Then we can extract the difference features, DF_2. A large modification can be detected easily from analysis of the variations in the reconstructed image (Fig. 5).

This fragile watermark method can detect not only slight changes but also large changes. When the host image is modified, the slight changes can be detected from the fragile watermark (F_1, F_2, F_3 , F_{M1}, F_{M2}, and F_{M3}), and the large changes can be detected from the reconstructed image (I_R and I_M)(Fig. 5).

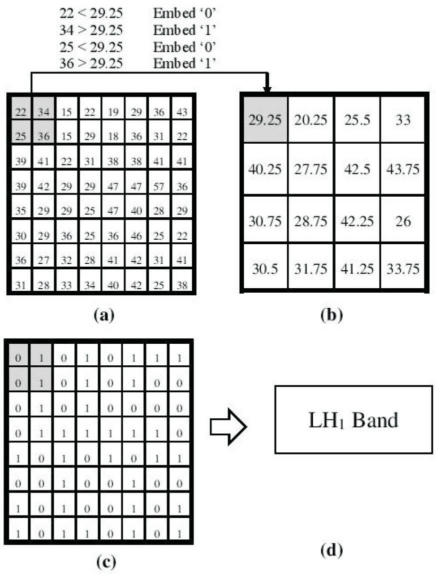


Fig. 4: Embedding the fragile watermark F_3 into the LH_1 band. (a) Wavelet coefficients (HH_1). (b) Let V_{ij} be the F_3 value. Comparing the wavelet coefficient with the average value. (c) Fragile watermark F_3. (d) Embedding the fragile watermark F_3 into the LH_1 band.

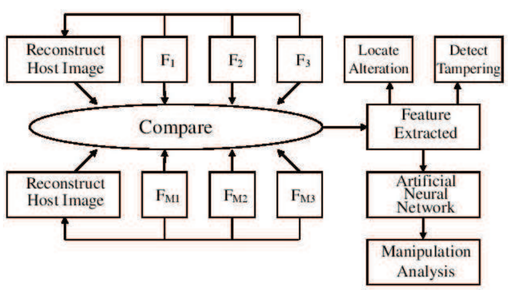


Fig. 5: Fragile watermark extraction and analysis.

Table 3: We Use Several Modification Features x_i as the Neural Network Input Vector.

Input	Modification Feature	Input	Modification Feature
x_1	Horizontal Distribution	x_{11}	Angle
x_2	Vertical Distribution	x_{12}	Geometric Factor #1
x_3	Size	x_{13}	Geometric Factor #2
x_4	Histogram Variation	x_{14}	Geometric Factor #3
x_5	Similarity	x_{15}	Spectrum Distribution
x_6	Quantization Factor	x_{16}	Shape Factor #1
x_7	Filter Factor #1	x_{17}	Shape Factor #2
x_8	Filter Factor #2	x_{18}	Correlation
x_9	Filter Factor #3	x_{19}	Noise Distribution Factor #1
x_{10}	Filter Factor #4	x_{20}	Noise Distribution Factor #2

Table 4: We Use Several Kinds of Modification Types d_k as Output Vector.

Output	Modification Type	Output	Modification Type
d_1	Image Cropping	d_{11}	Linear Geometric Transform
d_2	Salt and Pepper Noise	d_{12}	Median Filtering + JPEG
d_3	Scaling	d_{13}	Sharpening
d_4	Rotation	d_{14}	Rotation + Cropping
d_5	Blurred	d_{15}	Rotation + Scaling
d_6	Median Filtering	d_{16}	Rotation + JPEG
d_7	Gaussian Filtering	d_{17}	Scaling + Cropping
d_8	JPEG	d_{18}	Scaling + JPEG
d_9	Remove Row	d_{19}	JPEG + Cropping
d_{10}	Remove Column	d_{20}	Addtive Uniform Noise

Table 5: PSNR of Watermarked Images.

Fragile Watermarking						
IMAGE	Lena	Pepper	Baboon	Boat	Girl	Shuttle
PSNR (dB)	57.5	55.5	55.5	57.2	56.1	54.7

3 Artificial Neural Network Model

We use an artificial neural network to recognize what kind of modification has occurred [4, 7]. Given an input training pattern vector x_i and its desired output vector d_k, let ok denote the actual output vector. The index i is an input layer node. The index j is a hidden layer node. The index k is an output layer node. Let s denote the product of the weighting coefficients $\triangle W_{ji}$ and input features,

$$s_j = \sum_{i=1}^{I+1} w_{ji} x_i \tag{1}$$

The sum of the squared-error E is:

$$E = \frac{1}{2} \sum_{k=1}^{k=K} (d_k - o_k)^2 \tag{2}$$

Consider gradient descent, and adjust the weighting coefficients $\triangle W_{kj}$ backward between output layer and hidden layer, where η is the learning-rate parameter of the back-propagation algorithm.

$$\begin{aligned} \triangle W_{kj} &= W_{kj}(t-1) - W_{kj}(t) = -\eta \frac{\partial E}{\partial W_{kj}} \\ &= -\eta \frac{\partial E}{\partial o_k} \frac{\partial o_k}{\partial s_k} \frac{\partial s_k}{\partial W_{kj}} \\ &= -\eta(-(d_k - o_k)) f_k'(s_k) o_j \\ &= \eta(d_k - o_k) f_k'(s_k) o_j \end{aligned} \tag{3}$$

Adjust the weighting coefficients backward between hidden layer and hidden layer, or between hidden layer and input layer,

$$\begin{aligned}\triangle W_{ji} &= W_{ji}(t+1) - W_{ji}(t) = -\eta \frac{\partial E}{\partial W_{ji}} \\ &= -\eta \frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial s_j}\frac{\partial s_j}{\partial W_{ji}} = -\eta \frac{\partial E}{\partial o_j} f_j'(s_j) o_i\end{aligned} \tag{4}$$

$$\begin{aligned}\frac{\partial E}{\partial o_j} &= \frac{\partial E}{\partial s_1}\frac{\partial s_1}{\partial o_j} + \frac{\partial E}{\partial s_2}\frac{\partial s_2}{\partial o_j} + \cdots\cdots + \frac{\partial E}{\partial s_K}\frac{\partial s_K}{\partial o_j} \\ &= \frac{\partial E}{\partial o_1}\frac{\partial o_1}{\partial s_1}\frac{\partial s_1}{\partial o_j} + \frac{\partial E}{\partial o_2}\frac{\partial o_2}{\partial s_2}\frac{\partial s_2}{\partial o_j} + \cdots\cdots \\ &\quad + \frac{\partial E}{\partial o_K}\frac{\partial o_K}{\partial s_K}\frac{\partial s_K}{\partial o_K j} \\ &= -(d_1 - 0_1) f_1'(s_1) W_{1j} - (d_2 - 0_2) f_2'(s_2) W_{2j} \\ &\quad - \cdots\cdots - (d_k - 0_k) f_k'(s_k) W_{kj} \\ &= -\sum_{k=1}^{K} (d_k - 0_k) f_k'(s_k) W_{kj}\end{aligned} \tag{5}$$

$$\begin{aligned}\triangle W_{ji} &= -\eta \left(-\sum_{k=1}^{K} (d_k - 0_k) f_k'(s_k) W_{kj} \right) f_j'(s_j) o_i \\ &= \eta \left(\sum_{k=1}^{K} (d_k - 0_k) f_k'(s_k) W_{kj} \right) f_j'(s_j) o_i\end{aligned} \tag{6}$$

$$where \quad f(s) = \frac{1}{1-\exp(-s)} \quad f'(s) = f(s)(1-f(s)) \tag{7}$$

We adopt the back propagation model, as shown in Fig. 7. We get the difference coefficients (DF_1 and DF_2) from the fragile watermark and reconstructed image (Fig. 5). Next, we extract several important features according to the difference coefficients. We analyze the horizontal energy distribution, vertical energy distribution, size, histogram variation, and similarity (Table 3). We use these modification features, x_i, as the neural network input vector. We use several kinds of modification types, d_k, as the output vector (Table 4). After the initial values are set, the neural network begins training until it finds the optimal weights. After the neural network is established, we can use this model to analyze the degree of change, and in any modified image, the type of modification that has occurred.

We here provide an example to explain the modification features extraction. In Fig. 8(a), the image, "Lena", is attacked by image cropping. The fragile watermark detects the modification and presents the alteration (Fig. 8(b)). Then, the horizontal difference value is calculated from the fragile watermark and

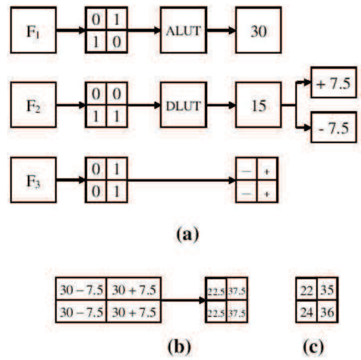


Fig. 6: Reconstructing the approximate host image. (a) We use original fragile watermarks (F_1, F_2, F_3) to reconstruct the approximate host image. (b) The approximate host image. (c) The original host image.

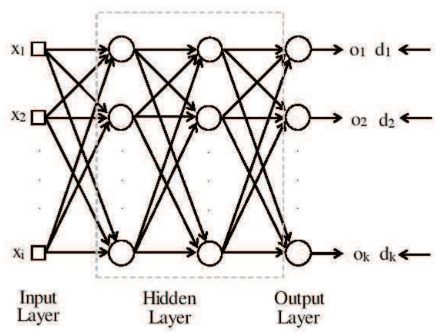
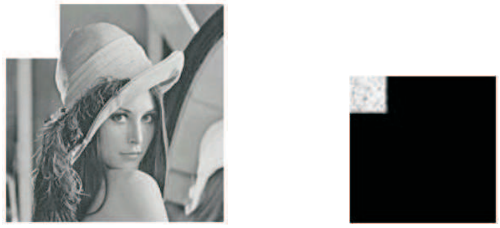


Fig. 7: Back propagation model of artificial neural network.

reconstructed image (Fig. 9(a)). Next, the horizontal distribution is estimated (Fig. 9(b)). The horizontal distribution factors are encoded (Fig. 9(c)). The modification features extraction is finished. We use these factors as the neural network input vector. The input vector is put into the neural network that has been trained. According to the characteristic of input vector, the neural network will analyze the type of modification.
The following describes the modification features x_i:

1) Horizontal Distribution: the horizontal distribution feature estimates the horizontal difference value between reconstructed host image (RHI) and modified image (MI). The ANN-based fragile watermark model can detect image cropping using horizontal distribution feature (Fig. 9(a)(b)(c)).
2) Vertical Distribution: the vertical distribution feature estimates the vertical difference value between RHI and MI. The ANN-based fragile watermark model can detect image cropping using vertical distribution feature.
3) Size: the size feature estimates the size change and detects resize attack.



(a) (b)

Fig. 8: (a) Host image attacked by cropping. (b) Fragile watermark detect the alteration.

Table 6: The Characteristics Comparison of several fragile watermark schemes.

	Fragile Watermarking					
Method	Proposed	Ding [3]	Lie [10]	Zhong [12]	Inoue [8]	Kundur [9]
Domain	DWT	DCT	DWT	Spatial	DWT	DWT
PSNR(dB)	57.5	56.5	35.9	51	37.8	43
Recognize Modification	Yes	No	No	No	No	No

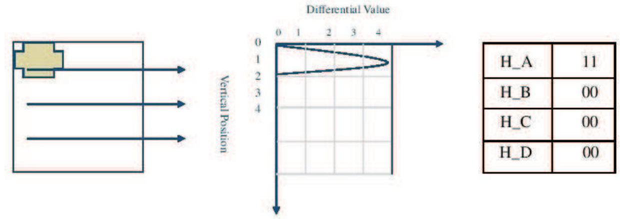
4)Histogram Variation: the histogram variation estimates the histogram of RHI and MI. Then the variation will be calculated by histogram variation feature.
5)Similarity: the similarity feature estimates the similarity between RHI and MI.
6)Quantization Factor: quantization factor estimates the average value of each block and evaluates quantization value. This factor can detect JPEG compression.
7)Angle: angle feature estimates image rotate angle between RHI and MI. This feature can detect rotation attack.
8)Geometric Factor: geometric feature estimate the geometric alteration between RHI and MI. This feature can detect the geometric attack.
9)Spectrum Distribution: spectrum distribution estimates the spectrum distribution in DWT domain and DCT domain.
10)Correlation: correlation feature estimate the correlation relation between RHI and MI.

4 Experimental Result and Discussion

4.1 Experimental results.

In order to prove the capabilities of the artificial neural network-based fragile watermarking scheme, a series of experiments were conducted.

We used our method to embed fragile watermarking into a host image. The fragile watermarks were embedded into the $HH_p(p=1,2,3\cdots)$ band, $HL_p(p=1,2,3\cdots)$ band, and $LH_p(p=1,2,3\cdots)$ band in the DWT domain.



(a) (b) (c)

Fig. 9: Modification features extraction (a) Calculat the difference from fragile watermark and reconstructed image. (b) Calculate the horizontal distribution. (c) Encode the horizontal distribution factors.

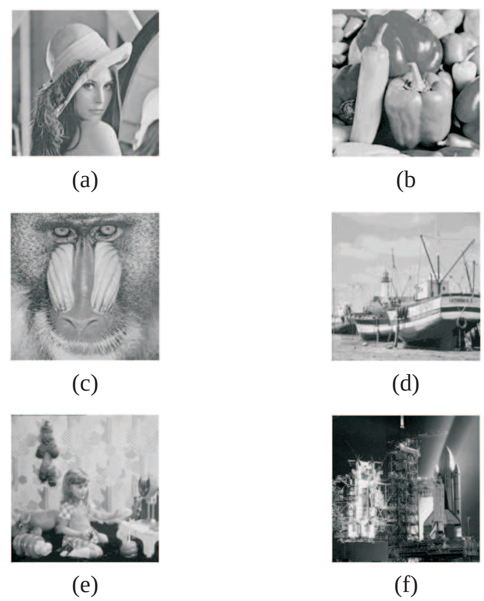


Fig. 10: Watermarked image (a)Lena (b)pepper (c)baboon (d)boat (e)Girl (f)shuttle.

Images of “Lena”, “pepper”, “baboon”, “boat”, “girl”, and “shuttle” were adopted for the simulation. The results are summarized in Table 5, where we computed the PSNR for each watermarked image (Fig. 10). The experimental results show that the watermarked images had high PSNR with a low degree of distortion. According to the results, the watermark is invisible. The comparison on PSNR between our method and other methods is shown in Table 6(using Lena image). Our method has high image quality.

To test the validity of our method, a tampering attack was performed. Fig. 11a shows the original “clock” image, and Fig. 11b shows the tampered image. The fragile watermark detects and locates the tampered regions according to the proposed scheme (Fig. 11c).

Table 7: Recognition Results for Modification Type.

Attack Type	Number of teaching pictures				
	50	100	150	200	250
Image Cropping	73 %	87 %	94 %	96 %	98 %
Salt and Pepper Noise	63 %	80 %	87 %	92 %	98 %
Scaling	96 %	100 %	100 %	100 %	100 %
Rotation	93 %	98 %	100 %	100 %	100 %
Blurred	61 %	69 %	76 %	84 %	93 %
Median Filtering	64 %	71 %	83 %	91 %	99 %
Gaussian Filtering	59 %	69 %	82 %	87 %	95 %
JPEG	56 %	67 %	79 %	87 %	93 %
Remove Row	83 %	94 %	100 %	100 %	100 %
Remove Column	81 %	92 %	99 %	100 %	100 %
Linear Geometric Transform	63 %	81 %	94 %	97 %	100 %
Median Filtering +JPEG	51 %	60 %	77 %	83 %	91 %
Sharpening	61 %	69 %	76 %	86 %	93 %
Rotation + Cropping	63 %	76 %	83 %	89 %	90 %
Rotation + Scaling	73 %	87 %	91 %	93 %	94 %
Rotation + JPEG	53 %	59 %	69 %	78 %	91 %
Scaling+Cropping	62 %	76 %	82 %	89 %	91 %
Scaling + JPEG	43 %	57 %	63 %	76 %	82 %
JPEG + Cropping	46 %	59 %	67 %	78 %	85 %
Addtive Uniforn Noise	65 %	81 %	88 %	93 %	98 %

(Unit: Recognition Rate %)

In the fragile watermark extraction process, we compared the fragile watermark and reconstructed the image. We extracted several features as inputs of the neural network input. We trained the neural network repeatedly until the optimal weights were found. Then we used several images attacked by StirMark 3.1 (http://www.cl.cam.ac.uk/ fapp2/watermarking/stirmark)[13].

This scheme can easy recognize blurred, scaling, median filtered, and Gaussian noise attacks and JPEG compression. This scheme can also recognize cropping attacks, salt and pepper noise attacks, slight changes, and so on. Our method has a high recognition ratio. The more experiments we do, the greater accuracy we attain. At first, we used 50 pictures to train the neural network. The average recognition ratios approached 65%. If we use 250 pictures to train the neural network, the average recognition ratios approach 95% (Table 7). The experimental results have proven that our method is indeed effective.

Because our fragile watermark is designed according to the characteristics of the host image, the fragile watermark can represent the original image. We can recognize what kind of alteration has occurred. After training the neural network, we can recognize any modification easily. Compared with other methods(Table 6), our method proposes alteration recognition technique to provide sufficient evidence for image authentication.

4.2 Discussion.

An artificial neural network-based fragile watermarking scheme is proposed in this work. There are some key characteristics are worthy of giving further discussion as follows.

Embedding the fragile watermark at LSB of wavelet coefficients just detects slight change in image. In order to solve this problem, our method establishes reconstructed image (I_R and I_M) to assist the fragile watermark (F_1, F_2, F_3 , F_{M1}, F_{M2}, and F_{M3}). This scheme can detect not only slight changes but also large changes. The slight changes can be detected from the fragile watermark (F_1, F_2, F_3 , F_{M1}, F_{M2}, and F_{M3}) and the large changes can be detected from the reconstructed image (I_R and I_M)(Fig. 5). On the other hand, the fragile watermark is extracted using the exclusive-or (XOR) operation without original image. This technique solves the traditional problem that a fragile watermark need original image to be extracted.

The artificial neural network is used to analyze the modifications. The experimental results show that the more the proposed method can recognize what kind of alteration has occurred. The reorganization results provide sufficient evidence for image authentication. It is the first paper to recognize the modification type adopting fragile watermark. This scheme is novel.

(a)

(b)

(c)

Fig. 11: The proposed fragile watermark detect the modification (a) Host image (b)Modified image (c)Fragile watermark detect the slight change.

5 Conclusions

A novel artificial neural network-based scheme for fragile watermarking has been developed in this work. This scheme analyzes the wavelet coefficients and encodes the characteristics of the host image. It easily detects even slight changes and has the ability to locate and characterize alterations without original image. We can use this artificial neural network model to analyze the degree of changes in any tampered image and identify what kind of alteration has occurred. This proposed algorithm was tested on many images and found to provide visually better-watermarked images. In particular, the proposed method shows a high recognition ratio in detecting the type of modifications. This scheme is not only novel but also feasible.

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