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Digital Watermarking Method Based on Nonsubsampled Contourlet Transform

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Abstract: The subbands in different scales and directions are obtained by image decomposition using the Nonsubsampled Contourlet Transform (NSCT). The multidirectional and redundancy of NSCT are employed to embed the watermark into the special subband. In order to eliminate the contradiction between imperceptibility and robustness, the watermark is adaptively embedded according to the human visual system. The blind detection can be accomplished based on correlation measurement. Geometric distortion is one of the most difficult attacks to image watermark system, since it can desynchronize the location of the watermark and causes fail watermark detection. The Scale-invariant Feature Transform (SIFT) is employed to against the scaling and rotation attacks in this study. Experimental results show that the scheme is effective and has high robustness against common attacks such as rotation, adding noise, filtering, cropping and JPEG compression.

Key words: Digital image watermarking, scale-invariant feature transform, nonsubsampled contourlet transform

INTRODUCTION

The fast progress of Internet and multimedia techniques makes them convenient to access the information but at the same time the multimedia security becomes a quite important problem. With the development of the internet of things and cloud computing, this problem becomes more urgent. As an effective method for the protection of digital property rights, content authentication and secret communication, digital watermark technology becomes an active research field. Digital image watermark embedding is commonly achieved by certain modifications to the host image. Given the embedding domain, the most traditional image watermark technology can be divided into two types: spatial domain and transform domain method. According to the spatial watermarking methods, the watermark information is directly embedded into original digital image, while the transform domain methods implement the watermark embedding in transform domain.

Generally, the spatial domain methods have advantages such as simplicity and high capacity, while the transform domain methods show more robustness (Chang and Hernandez-Palancar, 2009). The algorithms require the imperceptibility and robustness of watermarking technology to protect the intactness of the embedded information after environmental changes, certain processing operations or malicious attacks. It is still a hot point to design a fully satisfactory watermarking algorithm. Considering the mutual constraints and contradictions between the invisibility of watermark as well as its embedding capacity and robustness, the embedding strength becomes an important research issue for watermarking system. In order to balance the watermarking imperceptibility and robustness, some researchers optimize the embedding strength position or capacity using the machine learning methods. The neural networks was used to identify the optimum embedding strength and capacity of different image regions (Lou *et al*., 2003). Shieh presented a novel watermarking method based on Genetic Algorithm (GA) in the transform domain (Shieh *et al*., 2004). The genetic algorithm is used for optimizing the fitness function which includes both factors related to robustness and invisibility. Particle Search Optimization (PSO) algorithm is also used for watermark embedding (Li and Wang, 2007). Although these methods got some results but have some limitations, such as: “over learning”, the lack of unified mathematical theory and so on. Recent years, the support vector machine (SVM) has been applied in the watermarking technology. Fu embedded the template into the original image and then embedded the watermark in the same way. The SVM training model was obtained by the template samples and the output of SVM model is obtained and the watermark can be extract (Fu *et al*., 2004). and they improved the algorithm (Shen *et al*., 2005). At the embedding procedure, the support vector regression is trained using the information provided by the reference positions. Then the watermark is adaptively embedded into the blue channel of the carrier image. It can be extracted by virtue of the good learning ability of support vector machine. Tsai and Sun (2007) proposed a watermarking method based on SVM for image authentication (Tsai and Sun, 2007). It uses the set of training patterns to train the SVM and then applies the trained SVM model to classify a set of test patterns. Following the results produced by the classifier, this method retrieves the watermark information without the original image in watermark extraction process. These methods are useful but most of them can not against geometric distortion. A novel method is proposed (Wang *et al*., 2009). The Support Vector Regression (SVR) and Krawtchouk moments are utilized to correct the geometric distortion. The watermark is embedded by Pseudo-Zernike moments. The large calculation and high complexity are the drawbacks of this method. The Human Visible System (HVS) model is also used in the watermark embedding to enhance the imperceptibility of the technique (Tsai and Liu, 2011). However, most of them are not robust to geometric attack.

Geometric attack is still a difficult challenge. The watermark embedding and watermark detection are not synchronized if the watermarked image suffered geometric distortion. This study proposed a method using HVS and Scale-invariant Feature Transform (SIFT). By the trained HVS model, watermark information is embedded adaptively into the carrier image. The Nonsubsampled Contourlet Transform (NSCT) is utilized for the embedding and detection procedure. This method could against scaling and rotation attacks by virtue of the SIFT which is already implemented by hardware (Chang and Hernandez-Palancar, 2009). The rest of this study is as follows: The description of NSCT is over viewed in Section 2. Section 3 describes the geometric correction by SIFT. Section 4 covers the watermark embedding and detection procedure. The experimental results are showed in Section 5. Section 6 concludes this study.

NONSUBSAMPLED CONTOURLET TRANSFORM

The wavelet transform offers time-frequency and multistage analyze of the image. However, it couldn't represent the image effectively when the image contains smooth part in different directions. Contourlet transform improved this problem. Contourlet transform gives a multiresolution, local and directional expansion of images using Pyramidal Directional Filter Bank (PDFB). The PDFB combines Laplacian Pyramid (LP) with a directional bank. Since the sampling of DFB and LP in the transform procedure causes the aliasing and leakiness of frequency spectrum, the document (Da Cunha *et al*., 2006) has proposed the Nonsubsampled Contourlet Transform (NSCT), which retains the advantages of Contourlet transform and meanwhile suppresses the pseudo-Gibbs phenomenon. The nonsubsampled contourlet transform can be over viewed by Fig. 1.

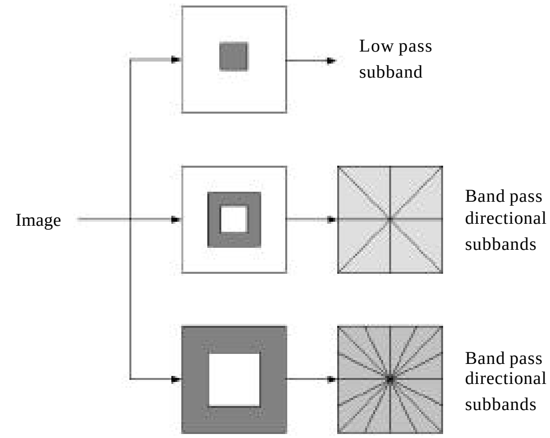

Fig. 1: Nonsubsampled contourlet transform

When the image undergoing NSCT, the energy is mostly concentrated in the edge and texture of directional sub bands of each scale. And the marginal probability distribution of directional sub band coefficients can approximately fit generalized Gassian model, with sharp peak appearing above the zero mean and two sides of the peak declining rapidly. If watermark information w (x, y) is a pseudorandom sequence of real numbers subjected to the distribution of N(0,1), the process of embedding watermark information into the directional sub band of NSCT can be perceived as a superposition of two signal volumes with the same distribution, so as to conceal mathematical statistics and meanwhile ensure the visual transparency.

SCALE-INVARIANT FEATURE TRANSFORM

The scale-invariant feature transform (SIFT) is a powerful feature point diction algorithm (Lowe, 2004). The good invariant of image rotation, scaling and translation can be achieved by means of SIFT. It is used widely and also can correct the geometric distortion. The basic idea of SIFT is to get features by a series of filtering operation to extract stable point in the image scale space. The SIFT feature points are detected both in undistorted image and distorted image and then the matched points are searched. In order to solve the scaling attack, the scale and central distance features of the matched points are used to calculate the scale distortion parameter and then the scale distortion is restored. In the meantime, the SIFT central angles of the matched points are obtained to restore the rotated distortion. The whole process can be described as:

- The function L (x, y, σ) is defined for the scale space of an image. It is obtained from the convolution of a variable-scale Gaussian function G (x, y, σ), with an input image I (x, y):

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y) \quad (1)$$

where, * denotes the convolution operation and:

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2} \quad (2)$$

D (x, y, σ) is utilized to obtain stable key point locations in the scale space. It can be calculated from the difference of two nearby scales separated by a constant multipartite factor k:

$$D(x,y,\sigma)=L(x,y,k\sigma)-L(x,y,\sigma) \quad (3)$$

- The next step is local extrema detection. It is implemented by comparing the pixel of difference of Gaussian images to its neighbors in the current scale and adjacent ones. It is chose only if it is larger than all of these neighbors or smaller than all of them

The next process is to implement a detailed fit to the nearby data for scale, location and ratio of principal curvatures after the key point candidate has been found by comparing a pixel to its neighbors. The points that have low contrast can be rejected by this information. The rejection to key points with low contrast is not enough to stability. The difference of Gaussian function will have a strong response along edges. Those unstable responded points will be rejected too.

- The main orientation of these key points should be obtained for the further operation. A region around the key point is used for the sample process. The statistical histogram of the gradient direction of neighborhood pixels is obtained. The peak of the histogram represents the principal direction of the key point. The gradient magnitude m and orientation θ are given by:

$$m=\sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2} \quad (4)$$

$$\theta=\tan^{-1}\left(\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}\right) \quad (5)$$

- The stable SIFT feature vectors are generated and they can be used to correct the scaling and rotation distortions. If the image is scaled s times, the number of matching points is n, the scale factor of key point P_i in the original image is d_i and the scale factor of the corresponding matching key point Q_i in the scaled image is q_i, then we can get:

$$s=\left(\sum_{i=1}^{n} q_i/d_i\right)/n \quad (6)$$

If the rotated angle is α, the number of matching points is n, the center angle of key point P_i in the original image is ϕ_i and the center angle of the corresponding matching key point Q_i in the rotated image is φ_i, then we can get:

$$\alpha=\left(\sum_{i=1}^{n}(\varphi_i-\phi_i)\right)/n \quad (7)$$

PROPOSED METHOD

Robust watermark can be embedded in approximation sub bands in middle or low frequency but changing approximation sub bands always leads to apparent distortion. Adaptively embedding watermark signals into the directional sub band with maximum energy after the NSCT process of the original image can maintain the balance between invisibility and robustness.

A watermark embedding:

- The low-pass approximation sub band I_L and directional sub band $C_{l,d}^{l?}$ will be obtained by conducting NSCT upon the original image I. L = 1, 2, ..., L and represents the NSP decomposition of the l th level and d represents the d th directional sub band of NSDFB transform of the l_λ scale
- To ensure certain embedding strength, the watermark information is embedded to the directional sub band with maximum energy. The sub band is marked as $C_{l,d}$ for convenience, with a size of M×N. Watermarking sequence w is a pseudorandom sequence of real numbers subjected to N(0,1) distribution with a length of M×N
- Watermark information can be adaptively embedded to the following equation:

$$C'_{l,d}(x,y)=C_{l,d}(x,y)+\alpha H_{l,d}(x,y)w(x,y) \quad (8)$$

where, $C'_{l,d}(x,y)$ is the modified value, $H_{l,d}$ (x, y) is the adaptive function and α is the embedding strength coefficient:

$$H_{l,d}(x,y) = F(l,d)\cdot B(l,x,y)^{0.2}\cdot T(l,x,y)^{0.2} \tag{9}$$

where, B (l, x, y) denotes the luminance property:

$$B(l,x,y) = \begin{cases} 2-L(l,x,y) & L(l,x,y) < 0.5 \\ 1+L(l,x,y) & \text{otherwise} \end{cases} \tag{10}$$

where, L (l, x, y) = I_l (x, y)/max (I_l).

F (l, d) denotes the frequency property:

$$F(l,d) = \begin{Bmatrix} \sqrt{2} & d=1 \\ 1 & \text{otherwise} \end{Bmatrix} \cdot \begin{cases} 1.00 & \text{if} \quad l=1 \\ 0.32 & \text{if} \quad l=2 \\ 0.16 & \text{if} \quad l=3 \\ 0.10 & \text{if} \quad l=4 \\ 0.05 & \text{if} \quad l\geq 5 \end{cases} \tag{11}$$

T (l, x, y) denotes the texture property:

$$\begin{aligned} &T(l,x,y) \\ &= \sum_{d}\sum_{x=0}^{1}\sum_{y=0}^{1} I_l(x,y)^2 \cdot \mathrm{Var}\{(I_l(l+i+x, l+j+y))\}_{\substack{i=0,1\\ j=0,1}} \end{aligned} \tag{12}$$

where I_l is the approximation sub band.

- NSCT is inversely implemented and the embedding process ends

B watermark detection:

- Conduct NSCT on test image I′ under detection and obtain the corresponding approximation sub bands and directional sub bands
- Find the directional sub band with maximum energy and then calculate the correlation values of watermark w and the directional sub band under detection:

$$\rho = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} C'_{l,d}(x,y)w(x,y) \tag{13}$$

- The threshold th is used to determine the existence of watermark: if ρ>th, the watermark exists; otherwise, it doesn't exist. The false detecting rate normally requires a much small number. If $P_f \leq 10^{-8}$ is required, then the threshold can be given by :

$$th = 3.97\sqrt{2\sigma_\rho^2} \tag{14}$$

Where:

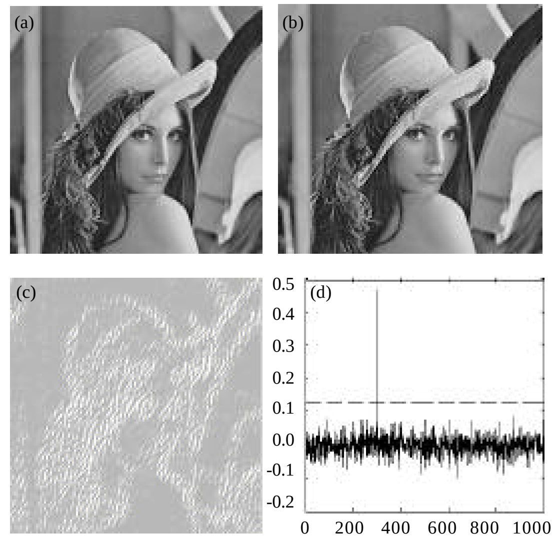

Fig. 2(a-d): Preliminary experiment result, (a) Original image, (b) Watermarked image, (c) Difference image and (d) Test result

$$\sigma_\rho^2 \approx \frac{1}{(MN)^2}\sum_{x=1}^{M}\sum_{y=1}^{N}(C'_{l,d}(x,y))^2$$

The test image should be geometric corrected by virtue of SIFT if it suffered scaling or rotation attack.

Since the watermark detection doesn't need the original image, it can be done blindly.

NEW HYBRID ARTIFICIAL BEE COLONY ALGORITHM

The gray Lena image is used as the original carrier image. The NSCT is implemented for two levels of pyramidal decomposition with four directional sub bands for each level. Watermark signal is a pseudorandom sequence subjected to N(0,1) distribution. 1000 sequences are created randomly and the 300th one is embedded. The original image, the watermarked image, the difference image and the detection result are showed respectively in Fig. 2a-d. From Fig. 2a and b, we may conclude that the algorithm presented in this study has good invisibility (the value of PSNR is 38.16).

The Gaussian noise, salt and pepper noise, cropping, filtering, JPEG compression, random printing attacks are tested and the results are shown in Fig. 3.

Table 1 shows the test results compared with the adaptive method in contourlet domain (Song *et al*., 2008) and the method based on SVR (Shen *et al*., 2005). From

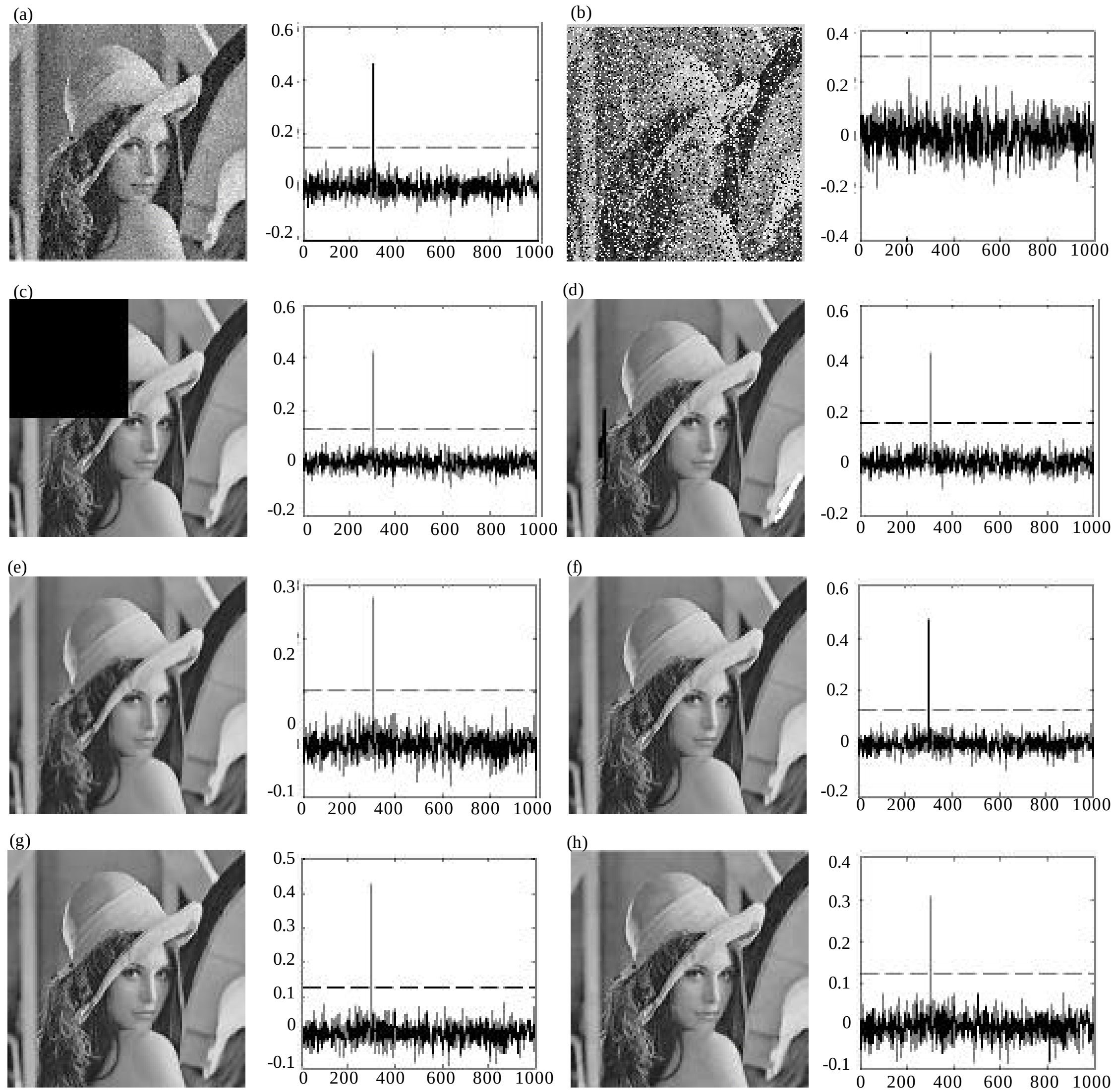

Fig. 3(a-h): Results of common processing operation, (a) Gaussian noise, (b) salt and pepper noise, (c) cropping, (d) Random printing, (e) Median filtering, (f) Average filtering, (g) JPEG (60) and (h) JPEG (15)

Table 1: Detection results

Rotation	This methods	Method by song	Method by Shen
Attacks	Pass	Pass	Pass
Gaussian noise	Pass	Pass	Pass
Salt and pepper noise	Pass	Pass	Pass
JPEG compression (QF = 40)	Pass	Pass	Pass
Average filtering	Pass	Pass	Pass
Median filtering	Pass	Fail	Pass
Cropping (25%)	Pass	Fail	Fail
Scaling (200%)	Pass	Fail	Fail
Scaling (50%)	Pass	Pass	Pass
Rotation (1°)	Pass	Fail	Fail
Rotation (120°)	This methods	Method by song	Method by Shen

Fig. 3 and Table 1, it is obvious that this method perform better in case of noise addition, filtering, cropping, JPEG compression, rotation, scaling and so on.

CONCLUSION

Image watermarking technology has been developed for decades but there are even many difficulties in the watermark system. The contradiction between the invisibility and robustness is still not easy to solve. In this study, the watermark embedding strength is related to the image content based on the human visible system. The nonsubsampled contourlet transform is employed as the embedding domain for its better property than wavelet and contourlet transform. The scaling and rotation distortions are solved by geometric correction using SIFT. Experimental results show that this method is robust to common image processing attacks.

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