Digital Watermarking Based on Interleaving Extraction Block Compressed Sensing In Contourlet Domain

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Abstract—**Traditional digital watermarking in transform domain computes complex and has limited anti-attack. Different ways of signal sparsity of compressed sensing represent different domains, which expands the embeddable space of watermarking. To take advantage of its multi-direction and multi-resolution characteristics to sparse image, Contourlet transform was analyzed. For the limitation of traditional block decision, we adopt the interleaving extraction to reduce the block artifacts. Furthermore, we presented the watermarking algorithm based on interleaving extraction block compressed sensing in Contourlet domain, simulation results verifies that the algorithm enhances the peak signal to noise ratio. Attack tests show that the proposed digital watermarking has better robustness against JPEG compression, noising, cutting etc.**

Keywords-Compressed sensing; Contourlet transform; Digital watermarking; Interleaving extraction

I. Introduction

Information technology plays an increasingly important role in resource exploitation, nation defense security and biomedicine etc. Therefore, the information security becomes more and more important. Digital watermarking technology attracts more eyes as a branch of information security. Generally speaking, the digital watermarking technology can be divided into two categories: space domain and transform domain. The algorithm in space domain is easy to operate, whereas, the robustness is poor. On the contrary, in transform domain, it has better robustness, whereas the calculation is complicated [1].

On the other hand, these two kinds of watermarking algorithms must satisfy Shannon's sampling theory while sampling, which makes a great pressure to image processing and requires people to establish new information description and processing theory framework for watermarking. The compressed sensing samples and compresses the data simultaneously, which compensates the drawbacks of watermarking, becomes a new research aspect [2-4]. The sparse decomposition of CS can expands the embeddable space of watermarking, improving the invisibility and robustness further. Furthermore, the measurement matrix can be considered as the key to enhance the security. Partial researches have been reported with reference to the combination of CS and watermarking [5-6]. Wei Liu et al. achieved the semi-fragile watermarking for image tamper detection. Haosheng Zhang et al. proposed the compressed sensing local image tamper detection in DCT domain through researching compressed sensing in information hiding. Yan Zhou et al. embedded measured value into the original image to improve the image tampering detection through LPDC coding. To our best knowledge, the most current work focus on the image tamper detection, few results have been published in improving the robustness. In this paper, we propose the interleaving extraction compressed sensing and apply it to the digital watermarking, aiming to improve the robustness of digital watermarking.

II. Related Work on Compressive Sensing

A. Encoding Observations and Measurements

Assuming that $N\times 1$ signal $f\in R^N$ is not sparse in the time domain, the linear observation process is considered as $y=\phi f$, where ϕ is a $M\times N$ matrix ($M << N$). If f is sparse under a set of orthogonal bases, then according to the formula $f=\psi x$, where ψ is the dimension of $N\times N$ orthogonal matrix, the sparse form or approximate sparse form of the transform domain coefficient x replaces the time domain form f , and y can be expressed as follows:

$$y = \phi f = \phi\psi x = \Theta x . \tag{1}$$

In Formula (1), the CS matrix $\Theta=\phi\psi$ is a $M\times N$ matrix, and the observation vector y is linearly superimposed by the signal sparse value in Θ [7].

We denote ϕ as the measurement matrix and ψ as the sparse decomposition matrix. The form of ϕ exists independently of signal f . ψ is composed of any set of orthogonal bases or compact frame. The set of orthogonal bases decomposes signal f into a sparse form and is only related to the reconstruction of the signal.

To ensure observed signals exist in a sufficiently sparse transform domain and then obtain CS measurements, we must determine a set of base vectors representing the original signal in sparse form. Considering the optimal performance of Contourlet transform in image sparse representation, we decide to realize image sparse decomposition in the Contourlet domain.

The Gaussian measurement matrix ϕ and $\psi = I$ are not correlated. Once ϕ is selected, regardless of what orthogonal matrix ψ is, the CS matrix will be an independent, identically distributed Gaussian matrix, with a high probability of meeting RIP. As a result, we select the Gaussian random matrix as the measurement matrix.

B. Decoding Reconstruction

For sparse coefficient vector x , if $\Theta x = y$, then for any vector r ($\Theta r = 0$) located in empty set space $N(\Theta)$ of Θ , all will have $\Theta(x+r) = y$. There should be infinite numbers of solution x' that satisfies $\Theta x' = y$ in Formula (1) when $M < N$. The reconstruction algorithm aims to find the sparsest coefficient vector x of the signal in the solution set space $H = N(\Theta) + x$. We apply the optimization algorithm to find the solution that best meets sparse conditions. In this study, we use l_1 norm minimization to reconstruct the original signal. The optimization equation is as follows:

$$\widetilde{\mathbf{x}} = \min \|\mathbf{x}'\|_1 \text{ so that } \mathbf{\Theta x}' = \mathbf{y} . \qquad (2)$$

It is a convex optimization problem that can accurately recover the sparse and approximate compressible signals. The greedy algorithm, which is the most widely used currently, is also used to solve l_1 norm minimization problem. This algorithm is between the convex relaxation method and combinatorial algorithm in operational efficiency, demand for observation values, and reconstruction precision.

C. Contourlet Transform

Contourlet transform is a multi-resolution, localized, and multi-directional real two-dimensional image representation method [8]. The support section of the base has a long strip structure. The aspect ratio of the strip structure changes based on scale, which is similar to the shape of the contour, and has an anisotropic scale. Among Contourlet coefficients, the energy of coefficients representing image edge is more concentrated, that is, the Contourlet transform for the curve exhibits a more sparse expression.

Contourlet transform separately analyzes multi-scale and direction. First, multi-scale analysis is performed using Laplacian Pyramid (LP) to identify singular points. The singular points are then synthesized by directional filter bank (DFB) in the same direction as a factor to capture high frequency components. Fig.1 shows the flow chart of Contourlet transform. LP also functions to avoid “leakage” of low frequency components because the directional filter itself is unsuitable for processing the low frequency part of the image. First, the original image is decomposed by LP to obtain low and high frequency images at each level. Then, LP decomposes the low frequency image, and the high frequency image is sent to DFB to obtain the sub-band information of each direction. Contourlet transform is different from other analytical methods because it features different numbers of decomposition directions at different scales. For example, the number of sub-bands of each level of decomposition is fixed in wavelet decomposition with only three directional sub-bands: horizontal, vertical, and diagonal. However, in Contourlet decomposition, the number of the sub bands in each level is exponentially two, and the number of the sub-bands varies.

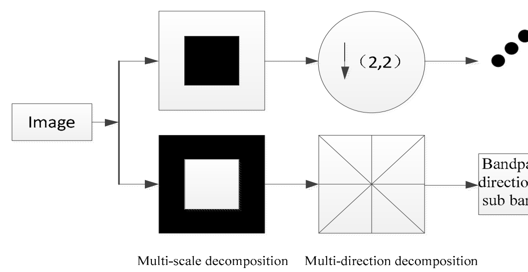


Figure 1. Basic flow of Contourlet Transform diagram

III. PROPOSED SCHEME

A. Block Compressive Sensing

The traditional CS method encounters several problems, such as high computational complexity, large memory size of compression sampling operator, and long reconstruction time. Block-based compressive sampling (BCS) can achieve better performance compromise and is widely applied in image acquisition. The computation of BCS is significantly less than that of traditional CS [9].

Consider an image I with size $I_r \times I_c$ of total pixels $N = I_r \times I_c$, we aim to obtain M measurement values. The image is divided into small $B \times B$ pieces in BCS. x_i represents the vector form of block i . Then, the corresponding observed value y_i is expressed as

$$y_i = \phi_B x_i . \qquad (3)$$

Where ϕ_B is a $m \times B^2$ matrix and $m = \lfloor MB^2 / N \rfloor$. For the entire image, the measurement matrix ϕ is a block diagonal matrix with the following form:

$$\phi = \begin{bmatrix} \phi_B & & & \\ & \phi_B & & \\ & & \ddots & \\ & & & \phi_B \end{bmatrix}. \tag{4}$$

In BCS algorithm, the $m \times B^2$ matrix ϕ_B needs to be stored, whereas the $M \times N$ matrix ϕ does not. When B is smaller, the storage space is smaller and is also achieved more quickly. By contrast, when B is larger, the reconstruction result is better. Based on experience, $B = 32$ is generally taken as the size of the block.

B. Interleaving Extraction

The BCS algorithm can greatly reduce computations with the reduced image block. However, BCS itself has many shortcomings. Despite a great advantage in the reconstruction speed, image quality declines.

The traditional block method reduces the quality of the reconstructed image to a certain extent, whereas interleaving extraction assigns any adjacent pixels in the image to different descriptions. Given the smooth gray variation in the adjacent pixels in natural images, each sub-image formed by interleaving extraction is of the same importance, and the correlation between each other is strong, which can be used to describe the original image [10]. Fig.2 shows the 2-Extraction, 4-Description using down-sampling decimation mode.

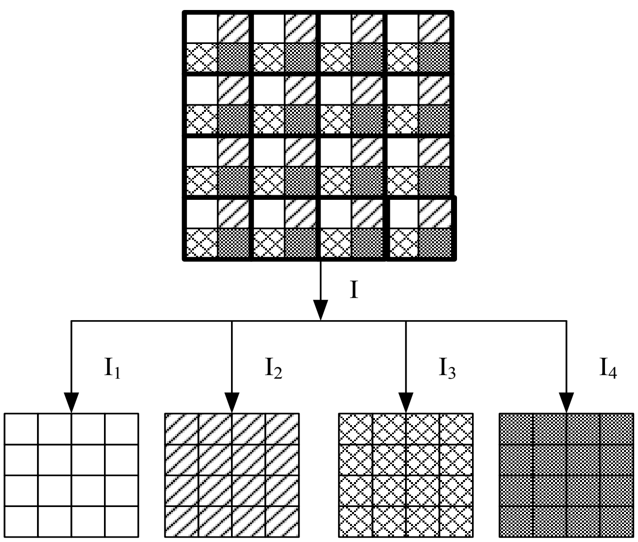


Figure 2. Image division by interleaving extraction

Fig.2 clearly shows that 2-Extraction generates a sub-image by extracting a pixel by every two rows and two columns. By analogy, n -Extraction extracts a pixel by every n rows and n columns. The procedure is equivalent to dividing the image into non-overlapping pieces of size $n \times n$, then sequentially assigning pixels to the sub-images. As a result, each image is a description.

C. The process and steps of algorithm

Fig. 3 shows the flowchart of watermarking embedding.

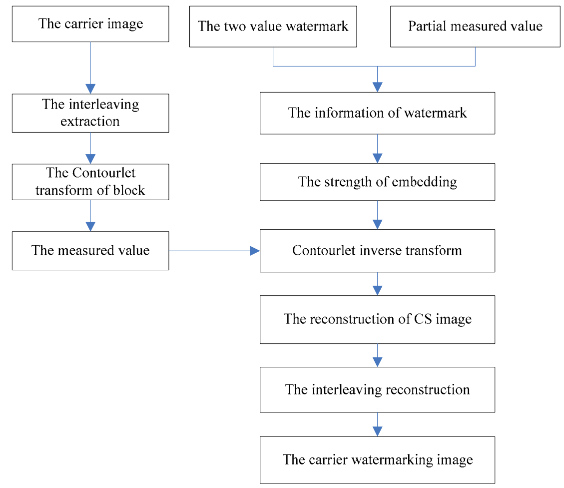


Figure 3. Flow chart of embedding watermark

The specific steps of embedding watermark are as follows.

(1) Partition the carrier image by interleaving extraction;

(2) Transform each sub-image by Contourlet transform, and obtain the measured values by using the Gaussian random matrix with different dimensions;

(3) Embed the binary value watermark combined with the appropriate measure value choosing by the size of the binary value watermark;

(4) Recover the image by the Contourlet inverse transform and reconstruct each sub-image by OMP;

(5) Recover the image by the inverse process of interleaving extraction.

Fig. 4 shows the process of watermark extraction, which is the inverse process of watermark embedding process.

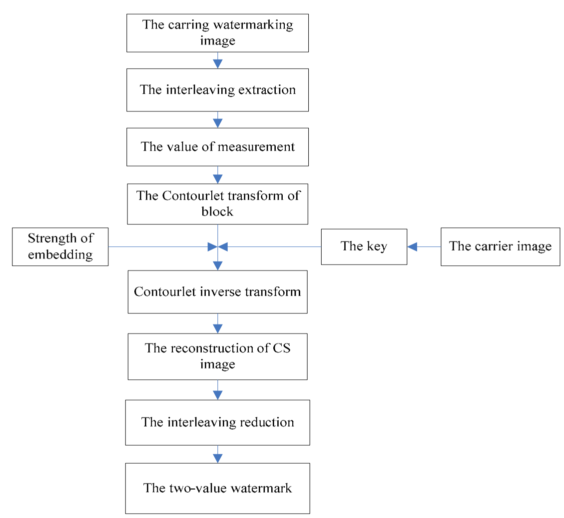


Figure 4. Flow chart of extracting watermark

The specific steps of extracting watermark are as follows:

(1) Partition the watermarked image by interleaving extraction block CS, and obtain the coefficient matrix in Contourlet domain;

(2) Compare the recovered coefficients with the original coefficients, and compute the extracted watermark according to the embedding strength and the measurement matrix;

(3) Perform the Contourlet inverse transform and OMP reconstruction to reconstruct the original watermark information.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Invisibility tests

To assess the validity of the proposed scheme, numerous experiments have been carried out. We choose Lena image as the carrier image, a binary-value image as the watermark image. We adopt “9-7” pyramid filter as the low pass filter and “pkva” as the directional filter in Contourlet transform. The layer of the decomposition for the input image is 4, and the directions of each layer are 1, 4, 8, and 16 respectively. We adopt 2-extraction, 4-description in interleaving extraction. The sampling rate is 0.7, and the strength of watermarking embedding is 0.1. We choose PSNR as the index to evaluate the invisibility in digital watermarking, NC as the difference between the extracted watermark image and the original watermark image.

Fig. 5 shows the carrier image, the watermarked image, the original binary-value watermark, the extracted watermark.

(a) Carrier Image

(b) Watermarked Image

(c) Original Watermark

(d) Extracted Watermark

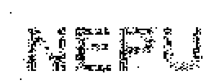
Figure 5. Images and Watermarks with no attacks

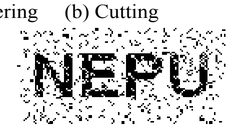
The PSNR is 43.7194. As a result, it is hard to distinguish the carrier image and the watermarked image. NC is 1.0, which verifies the validity of the proposed scheme.

B. Robustness tests

Different attacks have been performed to verify the robustness of the proposed scheme. Fig. 6 shows simulation results.

(a) Median Filtering (b) Cutting





(c) JPEG Compression (d) Salt & Peppers Noising

Figure 6. Watermarks with attacks

NCs by Extracted watermark are listed in Table 1.

TABLE I. NCS BY EXTRACTED WATERMARK

Attacks	Parameters	NC
Median Filtering	5*5	0.96
Cutting	50%	0.96
JPEG Compression	90%	0.61
Salt & Peppers Noising	0.01	0.67

V. CONCLUSION

Compressed sensing theory has the irreversible characteristics, and its sparse mode and measurement matrix are diverse. As a result, the process of sparse decomposition greatly expands the embedding space of transform domain for digital watermarking, improving the watermark invisibility and robustness. We proposed watermarking algorithm based on interleaving extraction block compression in contour domain. We adopted the interleaving extraction block to decrease the block effect, ensuring that the complexity of the observation process does not change along with the size of the image. Furthermore, it is easy to realize, and suitable for the treatment of high resolution image. In addition, the sparse representation of the image is realized by using Contourlet transform, which can effectively reconstruct details and texture information in the compressed sensing image reconstruction, improving the visual effect of the image to a certain extent.

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