

Digital Image Watermarking in Wavelet, Contourlet and Curvelet Domains

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ABSTRACT

In this paper a digital image watermarking algorithm in Wavelet, Contourlet and Curvelet transform domains is proposed. In the algorithm, original gray image is decomposed into coefficients in different sub-bands. For selected subband in each domain the watermark is embedded in the father nodes by relationship between father node and the maximum or minimum value of its child node. The experimental results show that the algorithm is invisible and robust against common image processing and attacks. Moreover it outperforms previous methods in the most situations.

Keywords: wavelet, contourlet, curvelet, watermark, father node, child nodes

1. INTRODUCTION

Nowadays computer networks and multimedia technologies are omnipresent and the transfer of electronic documents via these networks becomes inevitable. Digital watermarking is an effective copyright protection method. In a watermarking system the primary goal is to achieve a high level of robustness. Generally digital image watermarking has certain requirements, the most important being robustness and invisibility. Some information that the embedded watermarks like (Signature, Logo, ID number, etc) cannot be removed by attacks. The watermarking techniques are broadly categorized in two groups, the spatial domain and frequency domain [1,2,3]. One of the best way to transform in watermarking techniques is Discrete Wavelet Transform (DWT). But this technique do not possess the directional information such as directional edges of image. Contourlet Transform (CT) and Fast Discrete Curvelet Transform (FDCT) capable of capturing the directional information with multiresolution representation. In this paper a blind digital watermarking algorithm based on wavelet, contourlet and curvelet transform is proposed and compared together. The rest of paper is organized as follows: In section 2, about DWT, CT and FDCT are discussed. The image watermark embedding and extraction algorithm is given in section 3. Experimental results are presented in section 4. Section 5 draws conclusions.

2. DWT, CT and FDCT

2.1. Discrete Wavelet Transform

Amongst watermarking methods, Discrete Wavelet Transform (DWT) based ones are the most popular techniques. Using multiresolution decomposition methods, at first, the host image is transformed into several subbands. Then for concealing the watermark information in the host image, its bits are embedded into some selected subbands. In this embedding two facts must be considered: (i) Changing the wavelet coefficients in high frequency subbands somewhat results in image edge distortion; and the watermarking in these subbands has not a reliable robustness face to attacks (ii) Altering the wavelet coefficients in low frequency subbands significantly leads to image distortion since a high proportion of image information located in low frequency subbands [4]; The DWT is a powerful and a popular transform, which is familiar to image processing community. In two-dimensional applications, a given image is decomposed by DWT into four sub-bands (i.e. LL1, HL1, LH1, and HH1). The sub-band (LL1) is representative of the low frequency part where most energy is concentrated, while the other sub-bands display the high frequency content in the horizontal, vertical and diagonal directions. The sub-band (LL1) is further decomposed into other four sub-bands in order to obtain the next wavelet level. The required decomposition level is reached by the repetition of this process for several times [5,6]. An example of three-level wavelet decomposition sub-bands is shown in Figure 1 [6].

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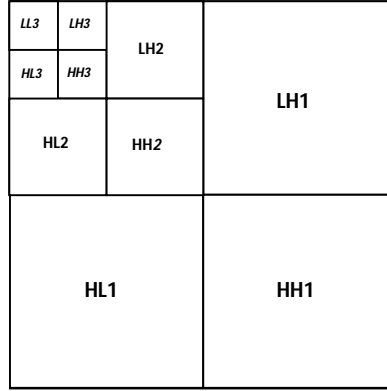


Figure 1. Three level DWT decomposition

2.2. Contourlet Transform

Do and Vetterli [7] introduced the contourlet transform as a new image decomposition scheme. Flat contours in different directions of an image can be represented in a more effective way by CT compared to those of the Discrete Wavelet Transform. The CT can be separated into two main steps: Laplacian pyramid (LP) decomposition and Directional Filter Bank (DFB) decomposition. LP decomposes the first image into low pass image and band pass image. Each band pass image is further decomposed by DFB step. Capture of smooth contours and directional edges is achieved through a DFB design. By repeating the same steps mentioned above, multi-resolution and multi-direction decomposition can be obtained for the low pass image. Wavelets do not possess directionality and anisotropy, which are the important properties of the contourlet and so wavelets are outperformed in many image processing applications by contourlet. A much richer set of directions and shapes are offered by contourlets compared to wavelets, and thus capturing smooth contours and geometric structures in images is conducted more effectively. A less effect in the quality of image is achieved by manipulating the values of coefficients in contourlet domain than in wavelet domain. Figure 2 shows the contourlet decomposition[6].

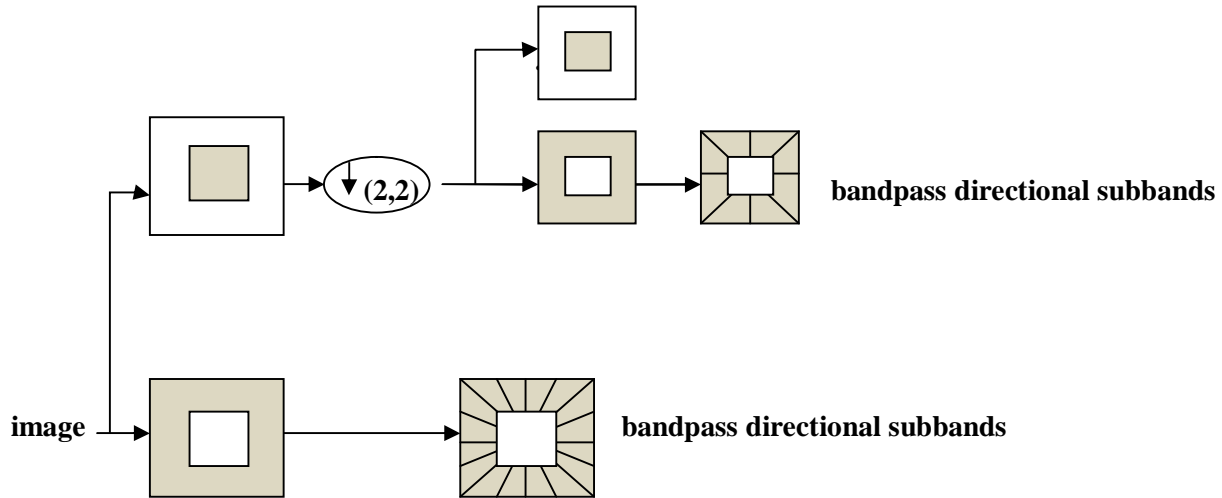


fig.2. Contourlet Decomposition- Laplacian pyramid followed by directional filter bank

The number of directional sub-bands at each level in contourlet is 2^n where n is a positive integer number. For example, we get 2, 4, 8, and 16 sub-bands if we choose to decompose an image into four levels using $n = (1, 2, 3, 4)$ as shown in figure 3[6].

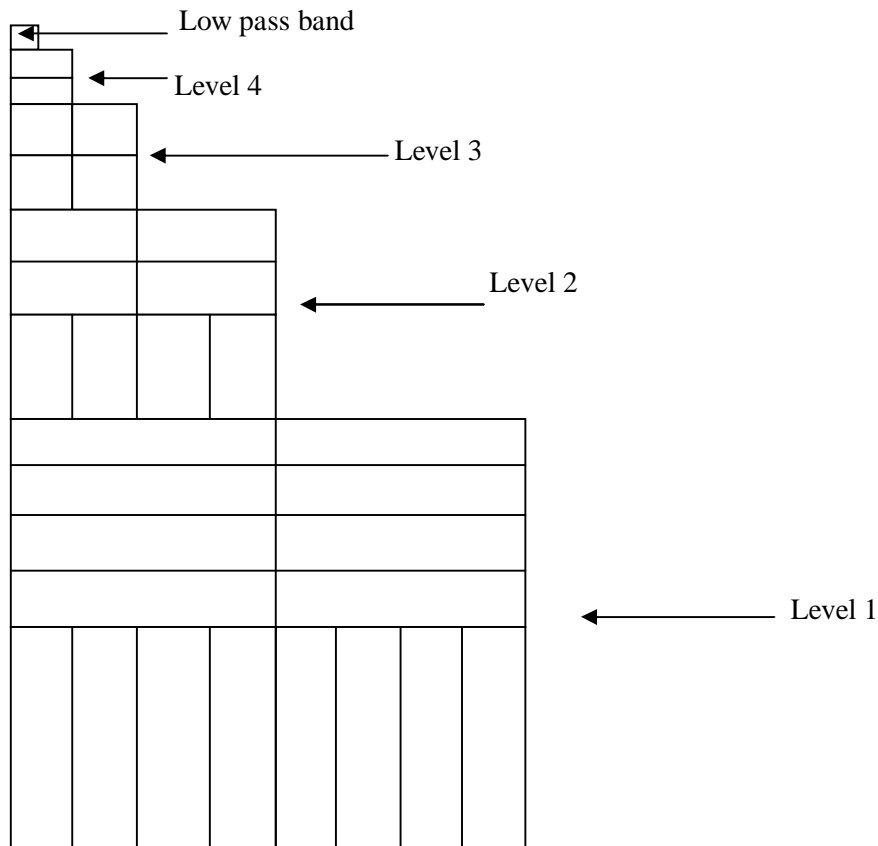


Fig.3. Contourlet Decomposition

2.3 Fast Discrete Curvelet Transform

In recent years, curvelet have been redesigned with a new mathematical architecture, which is simpler and easy to be implemented. It is known as Fast Discrete Curvelet Transform which is proposed by Candès and Donoho[8,9]. They suggested two new strategies, namely Unequi-Spaced Fast Fourier Transform (USFFT) and Frequency wrapping. The Wrapping based Curvelet transform techniques was found to be conceptually simpler, computed faster and less redundant than the previous techniques. Therefore, it is common to be used in researches implementing the curvelet transform. In this paper we focus on the wrapping DCT method.

Wrapping DCT Algorithm[10]:

1. Take FFT of the image
2. Divide FFT into collection of Digital Corona Tiles (Figure.4.a)
3. For each corona tile
 - (a) Translate the tile to the origin (Figure.4.b)
 - (b) Wrap the parallelogram shaped support of the tile around a rectangle centered at the origin (Figure.4.c)
 - (c) Take the Inverse FFT of the wrapped support
 - (d) Add the curvelet array to the collection of curvelet coefficients.

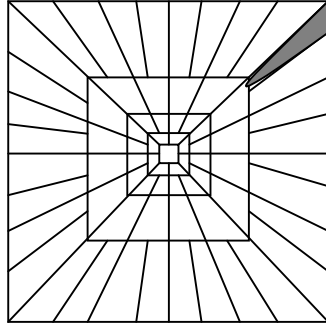


Fig4.(a)

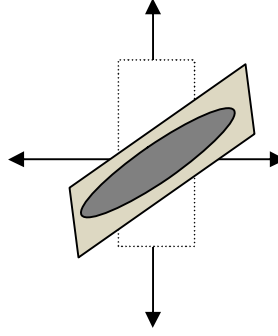


Fig4.(b)

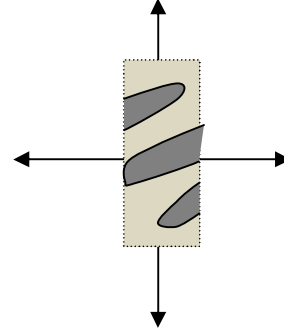


Fig4.(c)

3. Watermarking Algorithm

3.1 Watermark embedding in wavelet domain

In the embedding process a wavelet tree is established after the original gray image is decomposed by wavelet transform and some coefficients in the same sub-image are selected as father nodes. Every father node has child nodes in the same direction but different resolution sub-image. For each father node the maximum and minimum values of its child nodes are calculated and then every selected coefficient of father node is adjusted according to bits of watermark. Fig5 is shown the tree structure after an image decompose by two level wavelet transform. Haar wavelet is used in the process.

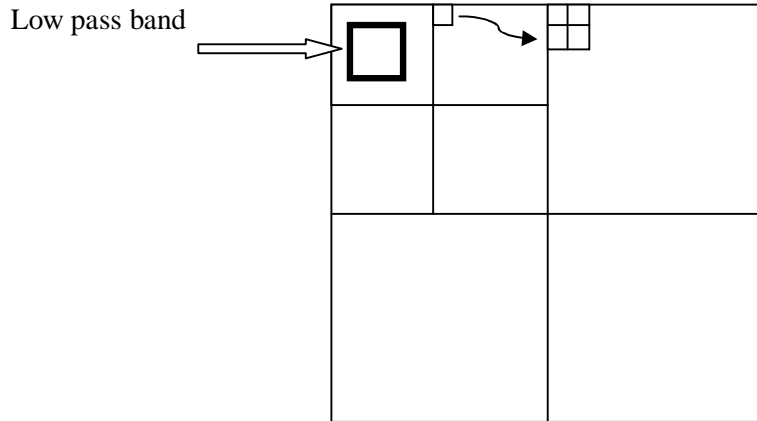


Fig.5. Structure of wavelet tree

The algorithm present selects coefficients in HL2 as father nodes and coefficients in HL1 as child nodes after the host image is decomposed two times by wavelet transform. In HL2 each father node has four child nodes in HL1

In the process of watermark embedding the coefficient in HL2 are selected and every bit of watermark image is embedded in HL2 as the relationship between father node and the maximum or minimum value of its child nodes is established. The process is as follows:

1) The binary watermark image $W = (A \text{ pixels} \times B \text{ pixels})$ convert to one-dimensional sequence (W^*) as a key (W, key) which will be used in the process of watermark extraction.

$$W^* = \{w_k^* | k = 1, 2, 3, \dots, A \times B; w_k^* = \{-1, 1\}\} \quad (1)$$

2) applying 2-level wavelet decomposition to the image we get 7 subbands HL1, LH1, HH1, LL1, HL2, LH2, HH2 and LL2.

$$3) \text{ if } x = \frac{M}{A} \quad y = \frac{N}{B} \quad (2)$$

M and N are the number of HL2's rows and columns respectively.

The locations (i, j) ($i = 1, 1 + x, 1 + 2x \dots, 1 + M - x$; $j = 1, 1 + y, 1 + 2y \dots, 1 + N - y$) in HL2 is selected to embed watermark. For each selected node in HL2 the coefficients of its child nodes in HL1 whose locations are $(2i - 2 + m, 2j - 2 + n)$ ($m = 1, 2$; $n = 1, 2$) and for each (i, j) the maximum and minimum value of child nodes selected. Then W^* is embedded as the following:

$$HL2(i, j) = \begin{cases} \text{maximum value of nodes} + \alpha; & W_k^* = 1 \\ \text{minimum value of nodes} + \alpha; & W_k^* = -1 \end{cases} \quad (3)$$

In the equation above $HL2(i, j)$ is the value of coefficient in HL2 band and the value of ' α ' can be changed to adjust the strength of watermark embedding.

4) Using the inverse wavelet transform the watermarked image is obtained.

3.2 Watermark extraction in wavelet domain

Watermark extraction is inverse to watermark embedding.

The extraction process is as follow:

1) The 'watermarked image' is decomposed after 2-level wavelet transform and the sub-images ($HL1^*$, $LH1^*$, $HH1^*$, $HL2^*$, $LH2^*$, $HH2^*$) which are the details of watermarked image are obtained.

$$2) x^* = \frac{M^*}{A}, y^* = \frac{N^*}{B} \quad (4)$$

M^* and N^* are the number of $HL2^*$'s rows and columns respectively.

According to each locations (i, j) ($i = 1, 1 + x^*, 1 + 2x^* \dots, M^* - x^* + 1$; $j = 1, 1 + y^*, 1 + 2y^* \dots, N^* - y^* + 1$) in $HL2^*$ selected one block (2×2) of coefficients in $HL1^*$. And the average value ($Mean^*$) of coefficients in each block is calculated.

3) The watermark $Out_W = \{Out_W_i | i = 1, 2, 3 \dots, A \times B\}$ is extracted as following:

$$Out_W_i = \begin{cases} 1 & \text{if } HL2^* \geq Mean^* \\ -1 & \text{if } HL2^* < Mean^* \end{cases} \quad (5)$$

4) The one-dimensional sequence Out_W is reorganized into two-dimensional image and then the watermark image Out_W^* is obtained with used the key (W_key).

3.3 Watermark embedding and extraction in Contourlet domain

The same as in the wavelet domain we define the tree structure for contourlet transform. Figure 6 shows two layer contourlet transform with 4 and 8 sub-images. The LP of contourlet transform adopts the '9-7' pyramid filter, because linear phase and the orthogonal of characteristics which make '9-7' more suitable for image processing, and the DFB are adopted 'pkva' direction filters.

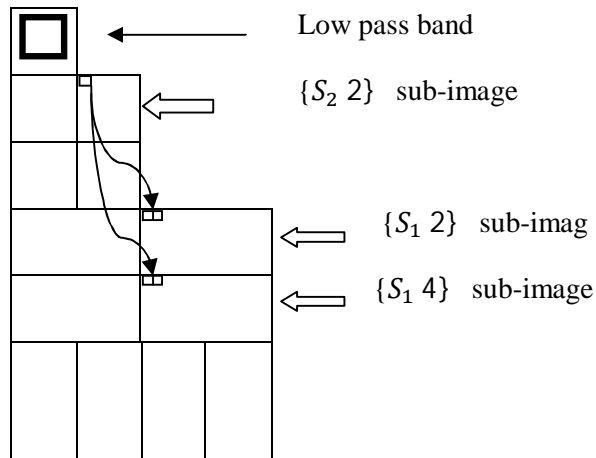


Fig6. Structure of contourlet tree

The detail sub-image ($\{S_2 1\}, \{S_2 2\}, \{S_2 3\}, \{S_2 4\}$;

$\{S_1 1\}, \{S_1 2\}, \{S_1 3\}, \{S_1 4\}, \{S_1 5\}, \{S_1 6\}, \{S_1 7\}, \{S_1 8\}$) in different resolution and different direction are obtained after the original image is decomposed by 2-layer contourlet transform and an approximative sub-image 'Low pass band' is also obtained.

The S_{22} is selected to embed watermark as father node and For each selected node in S_{22} the coefficients of its child nodes in S_{12} and S_{14} whose locations are $(i, 2j - 2 + n)(n = 1, 2)$ selected.

Then all of the steps are same embedding algorithm in wavelet domain and for extraction watermark for each locations (i, j) in S_{22} selected one block (1×2) of coefficients in S_{12}^* and one block (1×2) of coefficients in S_{14}^* and the other steps is the same extraction algorithm in wavelet domain.

3.4 Watermark embedding and extraction in Curvelet domain

When we used CurveLab 2.0 software package [11] output define as cells. The decomposition subbands by wrapping curvelet transform with 4 scales and 8 angles As the following:

$\{1 \times 1\}$: \leftarrow Low pass band

$\{1 \times 8\}$: $S_1^1, S_1^2, S_1^3, S_1^4, S_1^5, S_1^6, S_1^7, S_1^8$

$\{1 \times 16\}$: $S_2^1, S_2^2, S_2^3, S_2^4, S_2^5, S_2^6, S_2^7, S_2^8, S_2^9, S_2^{10}, S_2^{11}, S_2^{12}, S_2^{13}, S_2^{14}, S_2^{15}, S_2^{16}$

$\{1 \times 16\}$: $S_3^1, S_3^2, S_3^3, S_3^4, S_3^5, S_3^6, S_3^7, S_3^8, S_3^9, S_3^{10}, S_3^{11}, S_3^{12}, S_3^{13}, S_3^{14}, S_3^{15}, S_3^{16}$

For the binary watermark image $W = (A \text{ pixels} \times B \text{ pixels})$ in the process of watermark embedding the coefficient in S_2^3 are selected as father node.

$$\text{if } x = \frac{M}{A} \quad y = \frac{M}{B} \quad (6)$$

M is the number of S_2^3 's row.

The location (i, j) ($i = 1, 1 + x, 1 + 2x, \dots, M - x + 1$; $j = 1, 1 + y, 1 + 2y, \dots, M - y + 1$) in S_2^3 is selected to embed watermark. For each selected node in S_2^3 the coefficients of its child nodes in S_3^3 whose locations are $(2i - 2 + m, 2j - 2 + n)(m = 1, 2; n = 1, 2)$ and for each (i, j) the maximum and minimum value of child nodes selected. Then the other steps are same the embedding and extraction in wavelet domain.

4. EXPERIMENTAL RESULTS

The standard (512×512) gray-level wpeppers image is used as the host image. The watermark image (Logo) is a binary image with the size (16×32) pixels. Fig 7(a) is shown the host image and the watermark image in fig 7(b). the value of α in wavelet domain is (20) and in contourlet domain is (33) and in curvelet domain is (160). The image containing watermark using wavelet transform and the extracted watermark Out_W^* is shown in fig 7(c) and 7(d) respectively. The image containing watermark using contourlet transform and the extracted watermark Out_W^* is shown in fig 7(e) and 7(f) respectively. The image containing watermark using curvelet transform and the extracted watermark Out_W^* is shown in fig 7(g) and 7(h) respectively.

PSNR (Peak signal to noise ratio) is used to measure the invisibility of the embedded watermark in cover image and NC(normalized cross-correlation) is used to measure the similarity between the extracted watermark and the original watermark. PSNR and NC are given by:

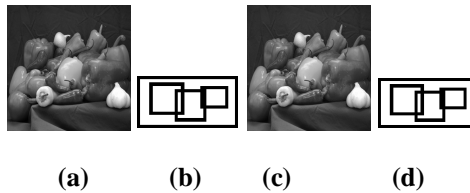
The size of host image "h" is $(M \times N)$

The watermarked image is h^*

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} |h(i, j) - h^*(i, j)|^2 \quad (7)$$

$$PSNR = 20 \log_{10} \left(\frac{255}{\sqrt{MSE}} \right) \quad (8)$$

$$NC = \frac{\sum \sum W \cdot Out_W^*}{\sqrt{\sum \sum W^2} \sqrt{\sum \sum Out_W^{*2}}} \quad (9)$$



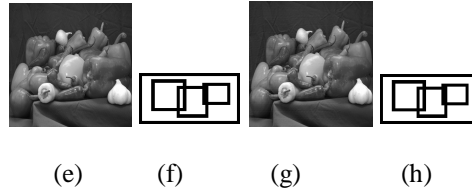


Fig7.(a)gray image, (b)watermark image, (c)watermarked image using wavelet transform with PSNR=46.49, (d)extracted watermark with NC=1,(e)watermarked image using contourlet transform with PSNR=44.60, (f)extracted watermark with NC=1,(g)watermarked image using curvelet transform with PSNR=39.85, (h)extracted watermark with NC=1.

Figure 8,9 and 10 show the PSNR and NC versus α in wavelet, contourlet and curvelet respectively.

The comparison PSNR and NC versus Quality Factor compression are shown in figure 11and 12 respectively. The experimental results of attacks on the watermarked image lena, wpeppers and wflower in wavelet transform domain is shown in table1 and comparing the proposed method in wavelet transform domain with Wang[12], Li[13], Lin[14] and [15]by Lena (512×512) gray image and watermark(16×32) using wavelet transform is shown in table2 and comparing the watermark extracted (16×32) in proposed method in wavelet, contourlet and curvelet transform domain by Lena (512×512) gray image is shown in table3 and comparing the proposed method in wavelet, contourlet and curvelet transform domain by Lena (512×512) gray image and watermark(16×32) is shown in table4. The comparing the proposed method in contourlet transform domain with Zhu[16] by Lena(512×512) gray image and watermark(32×32) is shown in table5 and watermark extracted(32×32) in contourlet transform domain by Lena(512×512) gray image is shown in table6.

The comparing the proposed method in curvelet transform domain with Zhang[17] and Thai[18] by Lena(512×512) gray image and watermark(16×16) is shown in table7 and watermark extracted(16×16) in curvelet transform domain by Lena(512×512) gray image is shown in table8.

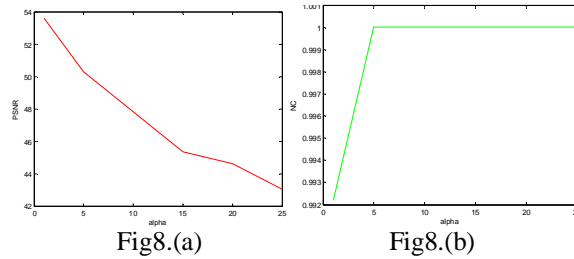


Fig8.(a) PSNR versus α in wavelet domain. Fig8.(b) NC versus α in wavelet domain

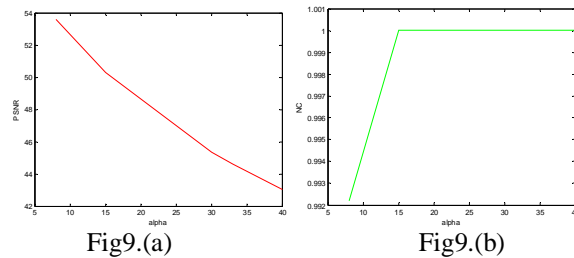


Fig9.(a) PSNR versus α in contourlet domain. Fig9.(b) NC versus α in contourlet domain

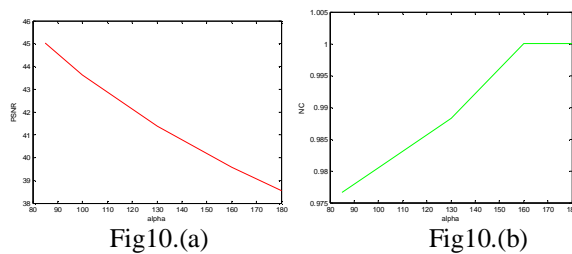


Fig10.(a) PSNR versus α in cuuveletdomain. Fig10.(b) NC versus α in curvelet domain

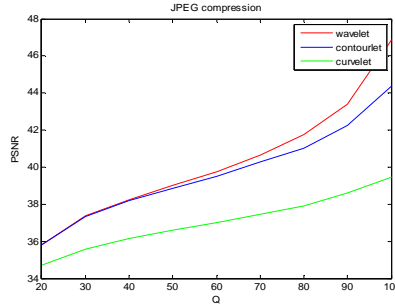


Fig11. PSNR versus Quality Factor Compression

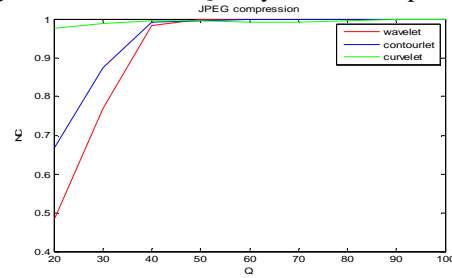


Fig12. NC versus Quality Factor Compression

Table.1. The comparing (NC) in wavelet transform domain for Lena, wpeppers and wflower gray images

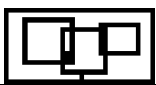


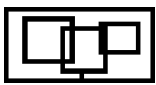
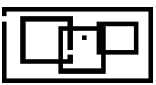
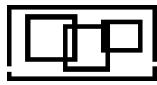
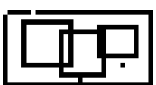


20	10	JPEG compression QF
0.60	0.30	NC/Lena
0.34	0.28	NC/wpeppers
0.40	0.30	NC/wflower
40	30	JPEG compression QF
0.98	0.80	NC/Lena
0.98	0.75	NC/wpeppers
0.99	0.75	NC/wflower
60	50	JPEG compression QF
1	0.99	NC/Lena
1	1	NC/wpeppers
1	1	NC/wflower
90	70	JPEG compression QF
1	1	NC/Lena
1	1	NC/wpeppers
1	1	NC/wflower
Rotate		Attack
-0.25°	0.25°	
0.77	0.70	NC/Lena
0.85	0.65	NC/wpeppers
0.80	0.60	NC/wflower
Resize (Scale=0.5)	Cropping (1/4)	Attacks
0.94	0.80	NC/Lena
0.96	0.82	NC/wpeppers
0.95	0.82	NC/wflower
Average filtering		Attack
[3×3]	[5×5]	
0.91	0.40	NC/Lena
0.96	0.55	NC/wpeppers
0.94	0.33	NC/wflower
Salt and pepper noise		Attack
Strength=0.005	Strength=0.01	Strength=0.02
0.96	0.93	0.88
0.95	0.91	0.89
0.96	0.88	0.81
Speckle noise (Average=0)		Attack
Variance=0.005	Variance=0.01	Variance=0.02
0.91	0.82	0.70
		NC/Lena

1	0.99	0.99	NC/wpeppers
0.94	0.88	0.71	NC/wflower
Median filtering			Attack
[5×5]	[3×3]		
0.35	0.92		NC/Lena
0.32	0.93		NC/wpeppers
0.20	0.91		NC/wflower
Gaussian noise (Average=0)			Attack
Variance=0.001	Variance=0.002	Variance=0.003	
0.97	0.96	0.86	NC/Lena
0.95	0.88	0.84	NC/wpeppers
0.93	0.91	0.81	NC/wflower

Table.2. The comparing the proposed method in wavelet transform domain with Wang[12] Li[13], Lin[14], and [15] by **Lena**(512×512) gray image and watermark(16×32) using wavelet transform.

attacks	Wang (PSNR = 38.2dB)	Li (PSNR= 40.6dB)	Lin (PSNR= 42.02dB)	[13] (PSNR= 42.47dB)	Proposed method
Median filtering[3×3]	0.51	0.35	0.90	0.94	0.92
Median filtering[4×4]	0.23	0.26	0.76	0.70	0.60
Cropping (1/4)	NA	0.61	0.66	0.72	0.80
JPEG (QF = 10)	NA	0.15	0.34	0.21	0.30
JPEG (QF = 20)	NA	0.34	0.67	0.63	0.60
JPEG (QF = 30)	0.15	0.52	0.82	0.88	0.80
JPEG (QF = 50)	0.28	0.52	0.96	0.98	0.99
JPEG (QF = 70)	0.57	0.63	0.97	1	1
JPEG (QF = 90)	1	0.78	0.99	1	1
Rotate (Angle=0.25°)	0.37	0.46	0.59	0.77	0.70
Rotate (Angle=-0.25°)	0.32	0.50	0.60	0.77	0.77
Resize (Scale=0.5)	NA	0.35	0.88	0.62	0.94
Average filtering[3×3]	NA	NA	0.95	0.83	0.91
Histogram Equalization	NA	NA	0.79	NA	1
Gaussian noise (Average=0 and Variance=0.001)	NA	NA	NA	0.69	0.97

Table.3. The comparing the watermark extracted(16×32) in wavelet, contourlet and curvelet transform domain by **Lena**(512×512) gray image

Average filtering[3 × 3]			
Curvelet	Contourlet	Wavelet	
			
32.07	31.84	32.22	PSNR
0.9883	0.9453	0.9141	NC
JPEG compression QF=50%			
Curvelet	Contourlet	Wavelet	
			
34.92	35.29	35.94	PSNR
0.9961	0.9883	0.9922	NC
JPEG compression QF=20%			
Curvelet	Contourlet	Wavelet	
			
32.80	32.80	33.34	PSNR
0.9844	0.7305	0.6055	NC

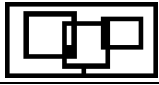



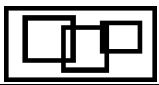



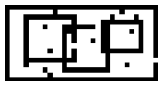

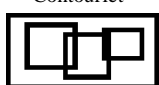

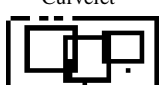

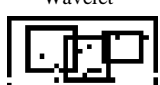
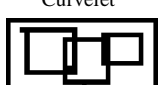


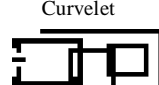
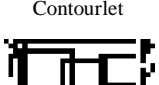
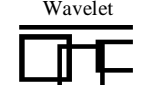
Median filtering[3 × 3]			
Curvelet 	Contourlet 	Wavelet 	
35.31	35.18	35.84	PSNR
0.9883	0.9492	0.9219	NC
Gaussian noise (Average=0 and Variance=0.001)			
Curvelet 	Contourlet 	Wavelet 	
5.71	29.80	29.85	PSNR
0.04	1	0.9727	NC
Salt and pepper noise (Strength=0.01)			
Curvelet 	Contourlet 	Wavelet 	
5.71	25.38	25.40	PSNR
-0.02	0.9492	0.9375	NC
Speckle noise (Average=0 and Variance=0.001)			
Curvelet 	Contourlet 	Wavelet 	
5.71	34.97	35.14	PSNR
-0.01	1	1	NC
Resize (Scale=0.5)			
Curvelet 	Contourlet 	Wavelet 	
32.92	32.60	32.98	PSNR
0.9570	0.9141	0.9414	NC
Rotate (Angle=0.25°)			
Curvelet 	Contourlet 	Wavelet 	
29.17	29.14	29.44	PSNR
0.9883	0.8828	0.7031	NC
Cropping (1/4)			
Curvelet 	Contourlet 	Wavelet 	
11.78	11.79	11.79	PSNR
0.8242	0.6992	0.800	NC

Table.4. The comparing the proposed method in wavelet, contourlet and curvelet transform domain by **Lena**(512×512) gray image and watermark(16×32)

attacks	Proposed method		
	Wavelet	contourlet	Curvelet
Median filtering[3×3]	0.92	0.94	0.98
Cropping (1/4)	0.80	0.69	0.82
JPEG (QF = 10)	0.29	0.30	0.50
JPEG (QF = 20)	0.60	0.73	0.98
JPEG (QF = 30)	0.80	0.93	0.98
JPEG (QF = 50)	0.99	0.98	0.99
JPEG (QF = 70)	1	1	0.98

JPEG (QF = 90)	1	1	0.99
Rotate (Angle=0.25°)	0.70	0.88	0.98
Rotate (Angle=-0.25°)	0.77	0.84	0.96
Resize (Scale=0.5)	0.94	0.91	0.95
Average filtering[3×3]	0.91	0.94	0.98
Histogram Equalization	1	0.92	-0.25
Gaussian noise (Average=0 and Variance=0.001)	0.97	1	0.04
Salt and pepper noise (Strength=0.01)	0.93	0.94	-0.02
Speckle noise (Average=0 and Variance=0.001)	1	1	-0.01

Table.5. The comparing the proposed method in contourlet transform domain with Zhu[16] by **Lena**(512×512) gray image and watermark(32×32).

Attacks	Zhu	Proposed Method
Median filtering(3×3)	0.93	0.96
Gaussian noise(0,0.001)	0.96	0.99
Gaussian noise(0,0.005)	0.68	0.86
Pepper&Salt noise (density 0.001)	0.99	0.99
Pepper&Salt noise (density 0.005)	0.88	0.96
Cropping (1/4)	0.84	0.68
JPEG(QF=40)	0.99	0.97

Table6.watermark extracted(32×32) in contourlet transform domain by **Lena**(512×512) gray image

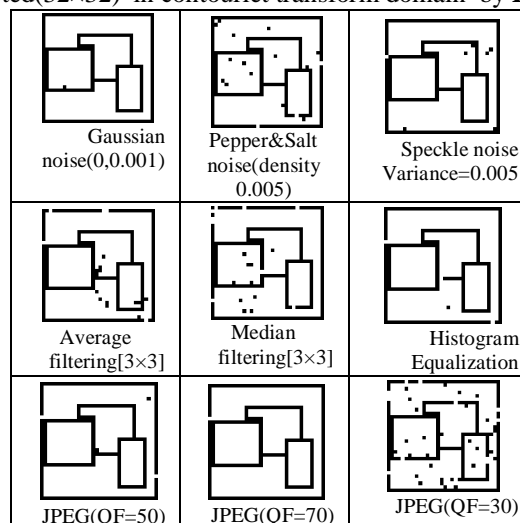
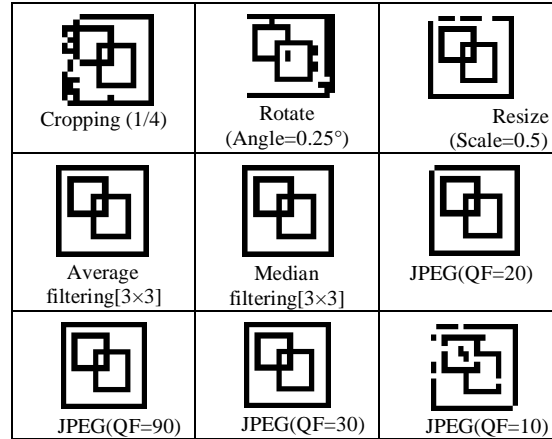


Table.7. The comparing the proposed method in curvelet transform domain with Zhang[17] and Thai[18] by **Lena**(512×512) gray image and watermark(16×16)

Attacks	Zhang	Thai	Proposed Method
Median filtering(3×3)	NA	0.85	1
JPEG(QF=15)	0.94	0.82	0.92
Cropping	NA	0.50	0.82
Lowpass filtering	0.97	0.75	0.99

Table8.watermark extracted(16×16) in curvelet transform domain by **Lena**(512×512) gray image



5. CONCLUSIONS

In this paper, a blind wavelet- contourlet- curvelet tree-based watermarking method is presented. We embed a watermark bit by quantizing the coefficients. The experimental results have showed that the algorithm has better invisibility and has stronger robustness when it is attacked by some attacks and a good resistance to many image attacks such as JPEG compression, filtering, and rotation

REFERENCES

- [1] Ali Al Haj, 2007, Combined DWT-DCT Digital Image Watermarking, J. Computer Science, Vol. 3, pp740-746
- [2] V. Potdar, S.Han, E.Chang, 2005," A Survey of Digital Image Watermarking Techniques" IEEE International Conference on Industrial Informatics,pp 709-716.
- [3] A.Piva, M.Barni, F.Bartolini,1998 " Copyright protection of digital image by means of frequency domain watermarking", SPIE Conference on Mathematics of Data/Image Coding, Compression and Encryption,pp.25-35.
- [4] Y. P. Hu and D. Z. Han, 2004 "Wavelet-based readable watermarking algorithm using adaptive quantization," Proc. IEEE Int. Conf. Image Machine Learning and Cybernetics, vol. 7, pp. 4076-4080.
- [5] Zhao, Wang ,Hu and Lian, 2009 "Digital Image Watermarking Algorithm Based on Wavelet Transform" Third International Symposium on Intelligent Information Technology Application, IEEE computer society
- [6] I.rube, M.nasr, M. naim, M.farouk, 2009, "Contourlet versus Wavelet Transform for a Robust Digital Image Watermarking Technique" , word academy of science, Engineering and Technology 60
- [7] Do, Minh N, Vetterli M. 2005 " The contourlet Transform: An efficient directional multiresolutional image representation", In IEEE transactions on Image Processing, Institute of Electrical and Electronic Engineers, New York, PP.2091-2106.
- [8] E.J.Candes, L.Demanet, D.L.Donoho, L.Ying, 2006 ,Fast Discrete Curvelet Transforms, SIAM Mult. Model. Sim.5-3(2006) 861899.
- [9] E.J.Canded and D.L.Donoho, 2004, New tight frames of curvelets and optimal representations of objects with piecewise-C2 singularities. Comm. On Pure and Appl. Math. 57(2004),219-266.
- [10] Tao.J , Xin.zh , 2008, " Research and application of image denoising method based on curvelet transform", the international archives of the phtogrammetry, remote sensing and spatial information sciences .vol.XXXVII:PART B2.
- [11] L.Ying,"CurveLab2.0, 2005, " California Institute of Technology.
- [12] Wang S.H and Lin Y.P ,Feb.2004 "Wavelet Tree Quantization for Copyright Protection Watermarking," IEEE Trans. Image Processing, vol.13,pp,154-165

- [13] E.Li, H.Liang and X.Niu, 2006," Blind Image Watermarking Scheme Based on Wavelet Tree Quantization Robust to Geometric Attacks", In Proceedings of the IEEE WCICA, vol.2,pp.10256-10260,doi: 10.1109/WCICA.2006.1714009.
- [14] Lin.W.H, Wang.Y.R, Horng.S, Kao.T, Yi Pan, 2009, A blind watermarking method using maximum wavelet coefficient quantization, *Expert Systems with Applications*, vol. 36, no. 9, pp.11509-11516.
- [15] M.J.Deighani, M.Hajizadeh and M.S.Helfroush, 2010,"Blind Watermarking Scheme Based on Remainder of Distance Vector of Wavelet Coefficients" *IEEE, International Conference on Signal Processing Systems(ICSPS)*.
- [16] S. m. Zhu, J. m. Liu, , 2009 "A Novel Blind Watermarking Scheme in Contourlet Domain Based on Singular Value Decomposition ", *Proc. WKDD '09*, vol.1, pp. 672-675.
- [17] Z.Zhang, H.Wei and J.Zhang, 2006 " Digital image watermark algorithm in the curvelet domain" *International Conference on Intelligent Information Hiding and Multimedia* pp.105-108
- [18] Thai .D .h, Kei.I, Harak.H, Chen.Y.W, Nagata.Y, Nagata.Z. 2007,"curvelet –Domain image watermarking based on edge embedding". *Leature notes in computer science* , vol,4693,pp.311-312