2008 International Symposium on Computer Science and Computational Technology

An Adaptive Watermark Scheme Based On Contourlet Transform

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Abstract--Based on the convergence and stability of the new mean shift fast algorithm, an adaptive watermark algorithm in contourlet domain based on mean shift texture features clustering is proposed in this paper. Through the texture recognition method based on gray co-occurrence matrix, watermark is embedded into the coefficients in contourlet domain, which makes the capability of the watermark more covert, anti-noise attack and robust. During the clustering, three texture features including energy, entropy and contrast were selected for mean shift fast clustering algorithm. Strong regional textures of host images are extracted directly, accurately and efficiently, and the embedding intensity can be gain automatically then. The experiment shows that this algorithm has the strong robustness to Gauss low pass filter, Wiener filter, median filtering, Salt and pepper noise, Gaussian noise, JPEG compression, shear attack etc. It is a blind detection, and adapt to various of images.

Key word--Mean Shift Clustering Algorithm；Contourlet Transform Domain；Gray Co-occurrence Matrix；Blind Watermark

I. INTRODUCTION

Due to the automatic and rapid convergence, the clustering algorithm has successfully applied to the digital watermark researches. Jianzhen Wu [1] proposed an HVS-based adaptive fuzzy clustering watermark algorithm in DCT domain. The image was seperated into the subsets which the watermark can be embedded into from those can not be embedded, and then embeds the watermark by modifying the intermediate-frequency coefficients. But for this algorithm, the scheme of localizing the watermark is simple, and the invisibility needs to be improved; Said E. El-Khamy[2] proposed a fuzzy clustering watermark algorithm based on human visual characteristic. The algorithm clusters the DC coefficients of the image in accordance with the energy size of AC, then calculates the JND value of each coefficient to embed watermark. For this algorithm, the watermark embedded positions are decided by the visual model, its robustness needs to be improved yet. Chip-Hong Chang [3] proposed a watermark algorithm in DCT domain based on Fuzzy-ART clustering method. The algorithm inputs the transformed coefficients in DCT domain which is regarded as the clustering characteristic, then modified the intermediate-frequency coefficients of the selected blocks to embed watermark, the complexity of the algorithm raised a lot, but its robustness improves just a little. It has been an urgent problem to design an algorithm with precise localization to the watermark, high efficiency and strong robustness.

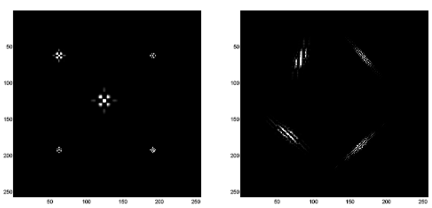
The mean shift algorithm is an effective statistical iterative algorithm [4]，which was first proposed by Fukunaga in 1975. The algorithm needs no any transcendental information, it completely depends on the sample points in feature space, it has fast convergent speed, so the algorithm has been widely applied to the computer visual domains including image segmentation[5] and track[6] etc this years, but it has not been reported to be applied to the watermark algorithm researches yet. Based on the high efficiency and the stability of the new-style mean shift clustering algorithm, this paper first tries to introduce the mean shift to the digital watermark research, and expects to bring strong robustness and fast convergent speed and better invisibility to watermark algorithms. The experimental simulation verifies the validity of the algorithm.

978-0-7695-3498-5/08 $25.00 © 2008 IEEE
DOI 10.1109/ISCSCT.2008.174

II. WATERMARK EMBEDDING STRATEGY

A、 Selection of transform domain

A good transform domain can make the watermark algorithm have stronger robustness and invisibility. Due to the abundant frequency layers, exquisite frequency partition and fast transform capability, the contourlet transform becomes a preferred choice. The contourlet transform is a new development of the wavelet transform, it is an expressing method with multi-scale, localized characteristic and multi-direction，it is a two-dimensional signal expressing method that can “really” catch the geometric structure. Comparing with the wavelet transform, the contourlet transform has a better effect in catching the detail. Fig.1 shows the radix of the two-dimensional wavelet transform and the contourlet transform respectively.



（a） （b）

Figure 1. Radix comparison between two-dimensional wavelet and contourlet transform

Fig.1 (a) shows the radix of the two-dimensional wavelet transform, Fig.1 (b) shows the radix of the contourlet transform. It is obviously that the contourlet transform provides more directions and shape information, so it is more effective to catch the smooth contour and the geometric structure of the image. The contourlet transform employs direction filter in high frequency, filtering on various directions makes the detailed characteristics on each direction retained. It brings two advantages: First, the analysis to the details of the contourlet transform makes the watermark directly attached to the details, namely the strong texture regions which the human vision is not sensitive to. It brings better invisibility; Second, the image details are shown as the coefficients with bigger magnitude in contourlet domain, so the embedded watermark can be directly located by these big coefficients, which makes the embedding process highly efficient and precise; Third, it reconstructs the image with the same number of important coefficients through non-linear approximation quickly, while the wavelet transform catches the contour by separate points slowly. So the contourlet transform can rapidly catch the contour by lines. When suffering from attacks, the contourlet transform can rapidly recover the watermark contour, which improves the watermark extracting quality and enhances the robustness. In addition, the important coefficient of the contourlet transform has another characteristic that, the random noises can produce the wavelet important coefficients similar to true edges of the image in visual, but it can not produce the contourlet important coefficient, which makes the contourlet transform a good application on the image de-noising. For the watermark processing, this characteristic can also improve the capability of the watermark in resisting various noise attacks such as Gauss noise etc. It brings a stronger robustness. On the basis of the experimental simulations and data results, this paper demonstrates that, the contourlet transform is more suitable to embed watermark than the wavelet transform, it has stronger robustness and better anti-noise capability.

III. ADAPTIVE EXTRACTION OF IMAGE STRONG TEXTURE REGIONS

From the human visual masking characteristic, we know that, the eye is insensitive to the changes in the strong texture regions of the image, so embedding watermark in the strong texture regions of an image can maximize the watermark embedding intensity and balance the robustness and the invisibility of the algorithm effectively.

The texture recognition method based on the gray-scale co-occurrence matrix represents the statistical characteristic of the image through the correlation in gray-scale value space. The gray-scale co-occurrence matrix are the probability density statistical characteristic on the condition of the two-rank combination of an image, which reflects the space information corresponding to the locations of a pixel pair. Hralick extracted 14 values of texture feature from the gray-scale co-occurrence matrix, which gained the quantitative description of the texture regions. Different texture regions can be measured by those values then. This paper selects three kinds of texture feature values including energy, entropy and contrast to measure the complexity of the texture. Energy measures the balance or smoothness of the whole image, entropy measures the amount of the information, and contrast measures the local changes in gray-scale. The experiments show that the three features are sufficient to distinguish the strong texture regions carefully. Further more, this paper cluster the blocks of the image which have the same complexity in texture by the mean shift clustering algorithm, and the clustered blocks are made as the watermark embedded position.

IV. WATERMARK EMBEDDING ALGORITHM

A. Embedding principle

On the basis of the above, a strong texture feature clustering algorithm was proposed based on the gray-scale co-occurrence matrix. The algorithm directly embeds the watermark in the strong texture region of the host image. It ensures the transparency of the algorithm, while can embed watermark with the biggest intensity. It ensures the robustness of the algorithm; The three texture features including energy, entropy and contrast based on gray-scale co-occurrence matrix can cluster the strong texture regions of an image by the mean shift fast clustering algorithm, which greatly improves the efficiency of the algorithm; Based on the stability of the big coefficients in contourlet transform domain and the good capability of catching contour, embedding watermark directly in the contourlet transform domain brings stronger robustness to the algorithm. Fig.2 is the watermark embedding schematic diagram, the embedding steps are shown as follows.

Step 1： Divide the original host image into 8*8 blocks, calculate the gray-scale co-occurrence matrix $P(i,j)$ of each block, where $P(i,j)$ is the number of the elements of the subset U.

$$U = \{(x,y) | f(x,y) = i \,\&\, f(x+DX, y+DY) = j; x,y = 0,1,2,\cdots N-1\}$$
$$i,j = 0,1,2,\ldots,L-1 \tag{1}$$

Where, x and y are the pixel coordinates of the image, $f(x,y)$ is the gray-scale level, L is the number of the gray-scale levels.

This paper selects three features including energy, entropy and contrast from the 14 texture features of the Hralick gray-scale co-occurrence matrix, which respectively shown as formula (2), (3), (4), which are used to quantitatively describe the texture features of the host image, then selects the strong texture regions as the watermark embedded positions.

Energy $$A_{SM} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\{p(i,j)\}^2 \tag{2}$$

Contrast $$C_{ON} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}|i-j|\{p(i,j)\} \tag{3}$$

Entropy $$E_{NT} = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i,j)\lg p(i,j) \tag{4}$$

Step 2：Regarding the three-dimensional texture feature of each image sub-block as the eigenvector, which are clustered by the mean shift clustering algorithm, and gain the position of the image strong texture sub-block and the texture complexity α, mark them as matrix R, retain R as the secret key, which is used to locate the embedding positions and control the embedding intensity.

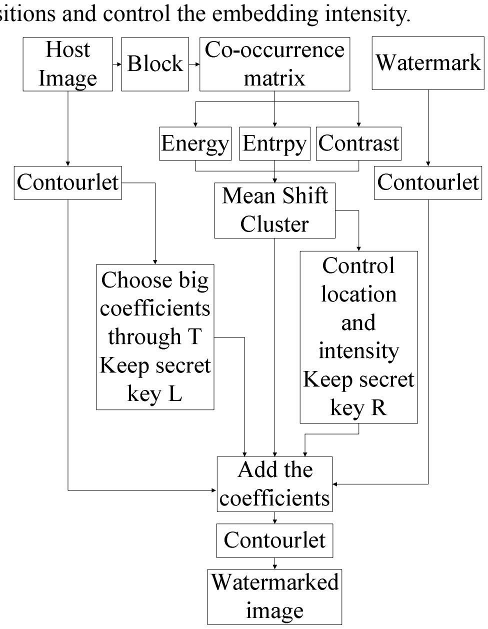


Figure 2. Watermark embedding schematic diagram

Step 3：Perform 4-layer contourlet decomposition to the host image I and 3-layer contourlet decomposition to the watermark image W. Considering that the anti-compression capability of the high-frequency part is bad and the eye is more sensitive to the low-frequency part, layer 2,3,4 of the host image are selected as the watermark embedded positions. As the coefficient with big absolute value directly represents the image texture and edge, embeding watermark in the big coefficients by layers can enhance the watermark embedding intensity and capacity, which will make the watermark energy equally superimposed on each frequency-band of the host image, and enhance the robustness of the algorithm. Specify as follows, calculate the energy E_l (l=2, 3, 4) of each sub -band on layer 2, 3, 4 of the host image I, shown as formula (5):

$$E_i = \sum (x_i)^2 \qquad (5)$$

Where, x_j represents all coefficients on the sub-band *j*, mark the sub-band B (i) of each layer by the size, i=1, 2, 3…n. Set the threshold T, select the coefficients that the absolute value are bigger than T as embedded object from the sub-band which has the biggest energy of each layer, mark the position as matrix L, retain L as the secret key, embed as formula (6).

$$I' = I + \alpha CW \qquad (6)$$

Where, C is a constant, α is the embedding intensity. If the region is a strong texture region, then determine by matrix R; if the region is smooth region, select α=0.3.

Step 4: Perform contourlet converse transform to the coefficient with watermark, reconstruct the image.

The watermark extracting algorithm is the reverse process of the embedding algorithm.

V. EXPERIMENTAL RESULTS

Experiment adopt 512*512 lena.bmp image as the host image, and a 64*64 binary imageas the watermark, the results are shown in Fig.3. The mean square error of the watermarked image is 10.2981, the PSNR can reach to 38.0032, and the watermarked image has no different subjective perception from the host image in the visual quality, it has better visual effect.

A. *Robustness test and analysis*

To test the robustness of the algorithm, we perform a series of attack tests, including: Gauss low-pass filter, Wiener filter, median filter, salt and pepper noise, Gaussian noise, JPEG attack, shear attack, etc, and evaluate the quality of the extracted watermark by the Normalized Cross-Correlation (NC) value, the Peak Signal to Noise Ratio (PSNR) value and the Mean Square Error (MSE) value, the results are shown in Table 1. Fig.3 shows the extracted watermark by our proposed algorithm under various attacks.

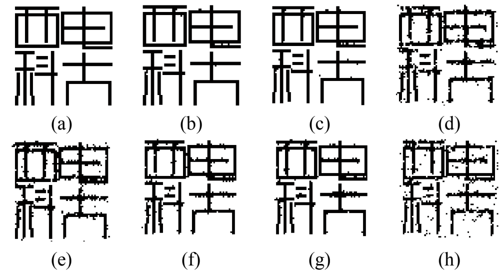


Figure 3. Fig.3 Extracted watermark by our proposed algorithm under various attacks. (a)original watermark; (b)without attacks ; (c) JPEG70; (d)JPEG20; (e)median 3*3window; (f)Wiener filtering 3*3window; (g)Gauss low-pass filtering 3*3window; (h)salt and pepper noise 0.01

NC represents the comparability between the original watermark W and the extracted watermark W^*, the closer to 1 NC is, the better the only certainty is. The calculating of NC is shown as formula (8).

$$NC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij} W_{ij}^*}{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij}^2 \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij}^{*2}}} \qquad (8)$$

As the assessment criteria of the image stability, PSNR has no any subjective factor.

$$PSNR = 10\log_{10}\frac{\max W_{m,n}^2}{MSE}(dB) \qquad (9)$$

Where, MSE is Mean Square Error:

$$MSE = \frac{1}{MN}\sum_{m,n}\left(W_{m,n} - W_{m,n}^*\right)^2 \qquad (10)$$

TABLE I. ATTACKING TEST OF OUR ALGORIGHM

Attack type	binary watermark attacking data of our algorithm		
	NC	***PSNR***	***MSE***
Gausss filter (3*3)	0.9453	10.4651	0.0898
Wiener filter (3*3)	0.9238	9.0309	0.1250
median filter (3*3)	0.8652	6.5427	0.2217
S&P (0.01)	0.8555	5.8542	0.2598
Gaussian (0.01)	0.6133	1.6027	0.6914
JPEG attack (70)	0.9922	16.6788	0.0215
JPEG attack (20)	0.8496	5.9700	0.2529
shear (100*100)	0.6426	3.5038	0.4463
rotate(450)	0.6543	3.2277	0.4756

(1) Filtering and JPEG compression

Fig.3 shows that, the watermark is still clear when suffering from filtering and compression, even if JPEG compression quality factor reaches to 20, namely strong damaging attack, NC value is still bigger than 0.84. It's because intermediate-frequency and low-frequency coefficients were selected to embed watermark. When suffering from various filtering and compression attacks, the intermediate-frequency and low-frequency energy loses less while the high-frequency energy loses more, so the ability of resisting various filtering and compression attacks of the algorithm is strong; On the aspect of the non-linear approximation, the algorithm reconstructs the image by the same number of important coefficients. The contourlet transform can rapidly catch the contour by lines, when attacked, the algorithm can rapidly and clearly recover the watermark contour, which improves the watermark extracting quality.

(2) Noise attacks

Random noises do not produce important coefficients of the contourlet, which is an important characteristic of the contourlet transform. Due to this, the algorithm has strong robustness superior to other transform domains against noise attacks. Among all the attacks, the performance against salt and pepper noise attack is the best, when the attacking intensity of salt and pepper noise is 0.01, NC value still reaches to 0.8555, which is shown in table 1.

VI. CONCLUSIONS

A robust watermark algorithm in contourlet domain based on mean shift texture features clustering is proposed this paper. The robustness of the algorithm is obviously superior to the watermark algorithm based on FCM clustering and K-means clustering. It has strong robustness against various attacks including Gauss low pass filter, Wiener filter, median filtering, Salt and pepper noise, Gaussian noise, JPEG compression, shear attack etc; The algorithm employs the strong texture feature clustering algorithm based on gray-scale co-occurrence matrix, which well balances the transparency and the robustness of the algorithm. The main contributions of this paper are: the introduction of the mean shift fast algorithm has greatly improved the efficiency of the watermark algorithm; Embedding watermark in the contourlet transform domain makes the selection of the texture region more direct and accurate, and makes the algorithm more efficient, and has stronger robustness against noise attacks than in other transform domains; The extracting method for strong texture region of the image based on mean shift texture features clustering is proposed in this paper, this process is fast, accurate and adaptive to various images; The algorithm achieves the blind detection.

REFERENCES

[1] Jianzhen Wi andJianyig Xie, adaptive image watermarking scheme based on HVS and fuzzy clustering theory[C], IEEE Int. Conf. Neural Networks & Signal Processing, December 14-17, 2003: 1493-1496

[2] Said E. El-Khamy, Noha A. El-Yamny, A New Perceptual Image Watermarking Technique Based on Adaptive Fuzzy Clustering[C], 21" National Radio Science Conference (NRSC2004), (NTI) March 16-18, 2004, C30: 1-8

[3] Chip-Hong Chang; Zhi Ye; Mingyan Zhang; Fuzzy-ART based adaptive digital watermarking scheme[J], Circuits and Systems for Video Technology, IEEE Transactions, Jan. 2005, 15(1): 65-81

[4] Sudhir Rao, Weifeng Liu, Principe, J.C. de Medeiros Martins A., Information Theoretic Mean Shift Algorithm, Machine Learning for Signal Processing, 2006[C]. Proceedings of the 2006 16th IEEE Signal Processing Society Workshop, Sept. 2006: 155-160.

[5] Wenbing Tao, Hai Jin, Yimin Zhang, Color Image Segmentation Based on Mean Shift and Normalized Cuts[J], IEEE Transactions on Systems Man and Cybernetics Part B-Cybernetics. 2007, 37(5): 1382-1389

[6] Collins,Robert T.Mean-shift blob tracking through scale space[M].United States: Institute of Electrical and Electronics Engineers Computer Society, 2003: 234-240.

[7] Do, M.N., Vetterli, M., The contourlet transform: an efficient directional multiresolution image representation[J], Image Processing, IEEE Transactions, Dec. 2005, 14(12): 2091-2106