ROBUST IMAGE WATERMARKING BASED ON THE WAVELET CONTOUR DETECTION

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ABSTRACT

Robustness is one of the fundamental requirements for image watermarking. In this paper, we present a new approach of robust image watermarking based on the contour of a host image, which is detected according to the Lipschitz singularity of the image. The watermark is embedded into the coefficients representing contours in the wavelet domain. Unlike other wavelet-based watermarking techniques which embed data into middle frequency bands and leave the low frequency coefficients untouched to avoid significant distortion, the new method embeds a watermark into the low pass frequency band after wavelet transform of the host image to provide more robustness while the distortion is still invisible. Numerous simulations demonstrate that the presented approach is highly robust to JPEG compression, white noise and linear filtering.

1. INTRODUCTION

Due to the open environment of Internet downloading, a new set of challenging problems are introduced in copyright protection regarding security and illegal distribution of privately owned images. One potential solution for declaring the ownership of images is using digital watermarks. Digital watermarking techniques solve the copyright protection problem by embedding ownership information inside an image and it has been under much research recently.

Many digital watermarking algorithms have been proposed. According to their casting/processing domain, , these contributions can be categorized into two classes: spatial-domain watermarks and transform-domain watermarks. Spatial domain techniques [1] embed watermarks in the least significant bits (LSB) by directly modifying pixels. They generally require a low computational cost and are generally easy to implement. For transform-domain techniques, an image transform, such as discrete cosine transform (DCT) [2] or discrete wavelet transform (DWT) [3-4], is employed and then a watermark is added to the transform coefficients according to the characteristics of human visual system (HVS). Compared to spatial-domain techniques, transform-domain techniques can embed more bits of a watermark and are more robust to attacks; thus, they are more attractive than spatial-domain methods.

In this paper, we present a novel transform-domain watermarking approach based on the contour of host image detected using wavelet singularity analysis. Unlike other wavelet-based watermarking techniques, which embed data into middle frequency bands and leave the low frequency coefficients untouched, the new method embeds a watermark into the low pass frequency band after wavelet transform of the host image to provide more robustness. The contour of image has mostly significant wavelet coefficients and its luminance change is not sensitive to human perception according to HVS, therefore, it provides more robustness to the watermark embedded. We first detect the contour of the approximated image resulting from the DWT; then the watermark is added on the wavelet coefficients of this contour. Finally, the watermark embedded contour is incorporated into the host image. The new approach is image adaptive in that the strength of the embedded watermark is controlled by the significance of the wavelet coefficients – the more significant are the coefficients, the more strength can the watermark be embedded.

2. ALGORITHM FOR CONTOUR DETECTION

In this paper, the contour of an image is detected based on the algorithm in [5], summarized as follows:

Let $f(x,y)$ represent a host image, and $\theta(x,y)$ is a low pass two-dimensional smoothing function. We define two wavelets $\psi^1(x,y)$ and $\psi^2(x,y)$ that are the partial derivatives of $\theta(x,y)$ along x and y, respectively, i.e.,

$$\begin{cases} \psi^1(x,y) = \frac{\partial \theta}{\partial x}(x,y) \\ \psi^2(x,y) = \frac{\partial \theta}{\partial y}(x,y) \end{cases}. \quad (1)$$

Let $\psi_s^i(x,y) = (1/s)^2 \psi^i(x/s, y/s),\ i = 1,2$ and for any scale s. The wavelet transform at each scale has two components:

$$\begin{pmatrix} W^1 f(s,x,y) \\ W^2 f(s,x,y) \end{pmatrix} = s \begin{pmatrix} f * \psi_s^1(x,y) \\ f * \psi_s^2(x,y) \end{pmatrix} = s \begin{pmatrix} \frac{\partial}{\partial x}(f*\theta_s)(x,y) \\ \frac{\partial}{\partial y}(f*\theta_s)(x,y) \end{pmatrix} = s\vec{\nabla}(f*\theta_s)(x,y), \quad (2)$$

where $W^1 f$ and $W^2 f$ represent the wavelet coefficients with respect to ψ^1 and ψ^2, respectively. The gradient vector operator is denoted by "$\vec{\nabla}$" and convolution by "*". At each scale s, the modulus and angle of the gradient vector can be written in the follows:

$$Mf(s,x,y) = \sqrt{\left|W^1 f(s,x,y)\right|^2 + \left|W^2 f(s,x,y)\right|^2}, \quad (3)$$

$$Af(s,x,y) = \begin{cases} \arg\tan\left(\frac{W^2 f(s,x,y)}{W^1 f(s,x,y)}\right), & W^1 f(s,x,y) > 0 \\ \pi - \arg\tan\left(\frac{W^2 f(s,x,y)}{W^1 f(s,x,y)}\right), & W^1 f(s,x,y) < 0 \end{cases}, \quad (4)$$

where $Mf(s,x,y)$ is the modulus value at scale s and $Af(s,x,y)$ is the angle between the gradient vector $\vec{\nabla}(f*\theta_s)(x,y)$ and the horizontal axis. This angle indicates the direction where the modulus Mf has the sharpest variation.

According to the Lipschitz singularity analysis in [6], it is proved that the edges in an image could be represented by its wavelet coefficient modulus maxima. In the new approach, for each point (s,x,y), $Af(s,x,y)$ is quantized with step size of $\pi/4$ to get two neighborhoods along the direction of Af. For example, if $Af(s,x,y)$ is $\pi/4$ after quantization, the two neighborhood of (s,x,y) will be $(s,x-1,y+1)$ and $(s,x+1,y-1)$. Denote $MMf(s,x,y)$ as the local modulus maxima at the point (x,y) in the scale s, i.e., $MMf(s,x,y)$ is set to be $Mf(s,x,y)$ when $Mf(s,x,y)$ is a modulus maximum along the direction given by $Af(s,x,y)$ and 0 otherwise.

In the presented new method, we choose the local modulus maxima in the finest scale, i.e., s=1, to represent the contours in an image. The contour image Cf of the original image f is then defined by the local modulus maxima in the wavelet domain, i.e.,

$$Cf(x,y) = MMf(1,x,y). \quad (5)$$

Note that the contour image is generated from the wavelet transform of the original host image. An example of contour detection on the Lena images is given in Figure 1.

3. CONTOUR BASED WATERMARKING APPRAOCH

The presented new method employs DWT again on the contour image (generated by the wavelet analysis of the host image). The watermark is first directly embedded into the wavelet coefficients of the contour image in high frequency bands. Finally, IDWT is applied to construct the watermarked image by incorporating the watermarked contour image.

The embedding process is illustrated in Figure 2, and it can be described by the following three steps.

Step1: Contour image construction

At the encoder side, the original image is undertaken M-level DWT [7] and decomposed into one approximation of image (LL) and M groups of high frequency bands (LH_i, HL_i, HH_i, $i=1,\ldots M$), where L and H denote low pass and band pass filters, respectively, and i represents the scale level.

We denote the LL_1 lowpass subband of original image as $g(x,y)$. By using the contour detection algorithm described in section 2, the associated contour $Cg(x,y)$ of $g(x,y)$ is obtained.

Step 2: Embed watermark in the contour image

Another DWT is applied to the contour image Cg. Then the coefficients in the bands at the finest scale (LH_1, HL_1, HH_1) are selected to embed the watermark. Denote the coefficients in HH_1 band as $W_{cg}(x,y)$ and suppose the contour image size is $N \times N$. Then the coefficients in HL_1 and LH_1 can be represented by $W_{cg}(x-N/2,y)$ and $W_{cg}(x,y-N/2)$, respectively. It is noted [7] that the wavelet coefficients of different subbands at the same scale level are highly correlated. Therefore, if $W_{cg}(x,y)>C$, then $W_{cg}(x-N/2,y)>C$ and $W_{cg}(x,y-N/2)>C$, where C is a threshold value for coefficient selection.

We choose a spread spectrum random bit sequence $w(i) \in \{0,1\}$ $(i = 1, \cdots L)$ as our watermark for its robustness to noise. The bit sequence is then undertaken a polar amplitude modulation with a constant Q as

$$w'(i) = \begin{cases} Q & w(i) = 1 \\ -Q & w(i) = 0 \end{cases}. \quad (6)$$

The length of the watermark, L_w, is less than the total number of selected coefficients. The selected coefficients are sorted by their significance and the watermark is embedded sequentially. The most significant coefficient is the first selected to embed watermark. The watermark is embedded into the selected wavelet coefficients of the contour image as follows:

$$\begin{aligned} W_{Cg}'(x_i, y_i) &= W_{Cg}(x_i, y_i) + \lambda_1 w'(i) \\ W_{Cg}'(x_i - N/2, y_i) &= W_{Cg}(x_i - N/2, y_i) + \lambda_2 w'(i), \\ W_{Cg}'(x_i, y_i - N/2) &= W_{Cg}(x_i, y_i - N/2) + \lambda_3 w'(i) \end{aligned} \quad (7)$$

where W_{cg}' denotes the watermarked wavelet coefficients of the contour image, and (x_i, y_i) is the position selected in HH_1 subband of the contour image after DWT, while $(x_i - N/2, y_i)$ *and* $(x_i, y_i - N/2)$ represent the corresponding positions in HL_1 and LH_1 subbands respectively. The constants λ_i $(i = 1,2,3)$ are empirically determined by HVS to get the best performance. In our approach, they are set as $\lambda_1 = 0.3, \lambda_2 = \lambda_3 = 0.35$. Taking IDWT of the W_{cg}', the watermarked contour image Cg' is obtained.

Step 3: Watermarked image construction

The LL_1 lowpass scaling subband of the host image $g(x,y)$ is modified by adding the watermarked contour image as follows:

$$g'(x, y) = g(x, y) + \beta Cg'(x, y) \quad (8)$$

where β is an empirical constants determined by balancing the robustness and watermark invisibility. Along with other wavelet subbands of the original host image, the watermarked image is then constructed by IDWT.

The above procedures are invertible to extract the watermark at the detector side given the known host image.

4. SIMULATION RESULTS

We conducted simulations on the Lena image of size 512×512. The spread spectrum binary sequence with length of 64 was embedded with our proposed approach. Three levels of DWT were performed on the host image and the low pass filter used to detect the image contour was a Gaussian low pass filter given by:

$$\theta(x, y) = \frac{1}{2}\exp(-x^2 - y^2). \quad (9)$$

Therefore, the two wavelets used to detect image contour can be derived as:

$$\begin{cases} \psi^1(x, y) = -x\exp(-x^2 - y^2) \\ \psi^2(x, y) = -y\exp(-x^2 - y^2) \end{cases}. \quad (10)$$

The original and watermarked images are shown in Figure 3. We can see the watermarked image is perceptually same to the original host. Simulation results show the robustness of this approach to JPEG compression and additive white noise. The robustness is evaluated by the correlation of the detected watermark and original watermark given by

$$\rho = \frac{\sum w(x)m(x)}{\sqrt{\sum w^2(x)}\sqrt{\sum m^2(x)}}, \quad (11)$$

where $m(x)$ is the detected watermark and $w(x)$ denotes the original watermark.

Figure 4(a) shows the simulation results of ρ under different JPEG compression ratio defined by the percentage of the image compressed, where compress ratio of 70% means compressed image quality is 30% of original one. Figure 4(b) gives the effects of additive white noise on the correlation coefficient. The image degradation level resulting from white noise is evaluated by peak-signal-to-noise-ratio (PSNR) given by

$$PSNR = 10\log\frac{\sum_{\forall(i,j)} 255\times 255}{\sum_{\forall(i,j)}[h(i,j) - f(i,j)]^2}, \quad (12)$$

where $h(i,j)$ and $f(i,j)$ denote noise corrupted image and original image respectively. Figure 4(c) shows the effects of linear mean filtering. We imposed the $K\times K$ (K=1, 3, 5, 7, 9) mean filters on the watermarked image. It is shown that even when K equals to 5, the watermark could still be detected with correlation coefficient of 0.98.

The simulations show that the watermark embedded by the presented new method is highly robust to common attacks such as JPEG compression, white noise and linear filtering, etc.

5. CONCLUSION

In this paper, we presented a novel robust approach of image watermarking based on the contour of the host image. Image singularity detection algorithm is applied to detect the contour image. The watermark is embedded into the contour image first and then incorporated into the low frequency scaling subband of the host image to ensure the robustness. The watermark strength is adjusted according to HVS. The proposed approach is highly robust to JPEG compression, white noise and linear filtering. Even when the attacked image is heavily destroyed, the watermark can still be detected. Future work will concentrate on making the approach more practical such as combining it with the JPEG2000 standard and improving it to blindly detect watermark without the knowledge of original images.

6. REFERENCES

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(a) (b)

Figure 1: (a) Original image f; (b) Contour of image Cf

(a) (b)

Figure 3: (a) host image (b) watermarked image, the PSNR after embedding is 51.2 dB

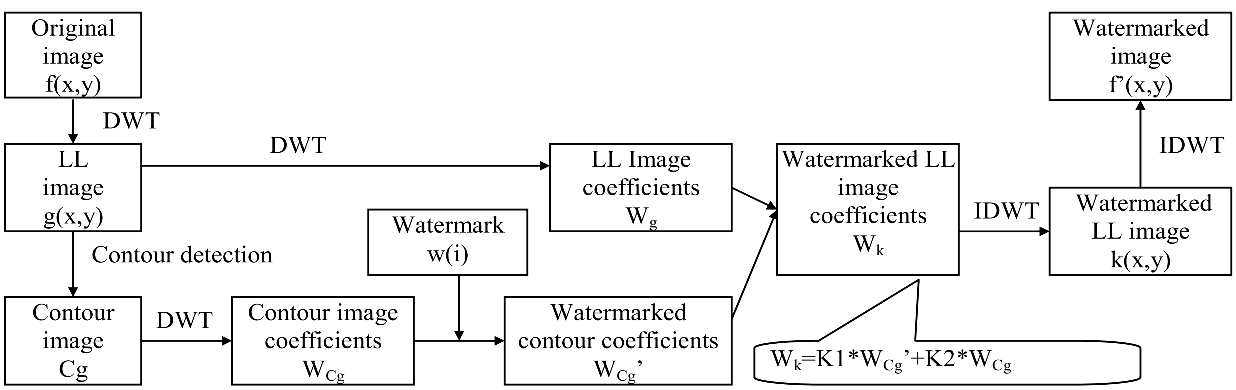
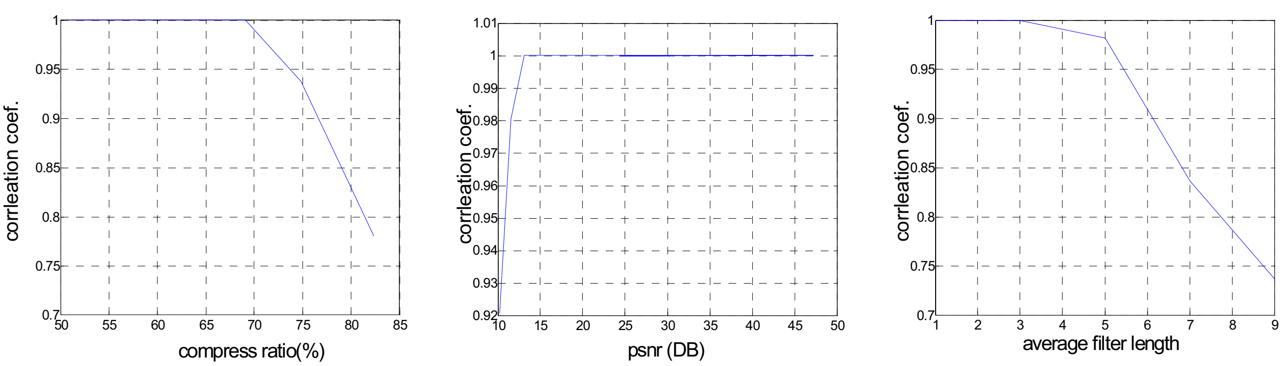


Figure 2: The proposed new watermarking approach



(a) (b) (c)

Figure 4: Correlation coefficients of the extracted watermark with the original by varying (a) compression ratios; (b) *PSNR*s due to white noise attack; (c) the average low pass filter ($K \times K$) length K