Local histogram based geometric invariant image watermarking

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Abstract

Compared with other existing methods, the feature point-based image watermarking schemes can resist to global geometric attacks and local geometric attacks, especially cropping and random bending attacks (RBAs), by binding watermark synchronization with salient image characteristics. However, the watermark detection rate remains low in the current feature point-based watermarking schemes. The main reason is that both of feature point extraction and watermark embedding are more or less related to the pixel position, which is seriously distorted by the interpolation error and the shift problem during geometric attacks. In view of these facts, this paper proposes a geometrically robust image watermarking scheme based on local histogram. Our scheme mainly consists of three components: (1) feature points extraction and local circular regions (LCRs) construction are conducted by using Harris-Laplace detector; (2) a mechanism of graph theoretical clustering-based feature selection is used to choose a set of non-overlapped LCRs, then geometrically invariant LCRs are completely formed through dominant orientation normalization; and (3) the histogram and mean statistically independent of the pixel position are calculated over the selected LCRs and utilized to embed watermarks. Experimental results demonstrate that the proposed scheme can provide sufficient robustness against geometric attacks as well as common image processing operations.

1. Introduction

Digital watermarking has been developed as a promising technology for image forensics, copyright protection, authentication, and fingerprinting [1,2]. In the image forensics scenario, digital watermark can be used as a tool to discriminate whether an original content is tampered or not. This kind of techniques for image forensics is commonly known as active detection techniques. Unfortunately, most present imaging devices do not contain such modules to embed watermarks. Thus, many passive detection techniques have been proposed from different aspects [3–7]. In the copyright protection scenario, robustness is the most essential issue to affect the performance of the watermarking system. Robustness means that the embedded watermark should be robust against various attacks and processing operations. Among these attacks, geometric attacks including global transformations and local transformations are still the most difficult problem to deal with. It is mainly because that geometric attack induces synchronization errors between the original and embedded watermark without having to remove the hidden information or degrade the quality of the watermarked content. In this paper, we focus on the digital watermarking for copyright protection.

The existing watermarking methods that are resistant to geometric attacks can be classified into exhaustive search, invariant domain, embedding template, and feature-based.
One concern in the exhaustive search is the computational cost in the larger search space. Watermarking techniques involving invariant domain usually suffer from implementation issues and are vulnerable to cropping. The embedding template-based techniques are vulnerable to template estimation attacks and cropping. By contrast, the feature-based watermarking schemes can resist against many various attacks including cropping and RBAs by binding the watermark synchronization with the image salient characteristics. These characteristics may be the whole image, some local regions, or feature points. This class of watermark synchronization techniques, also known as second generation watermarking [8], can be divided into three sub-categories: moment-based, histogram-based, and feature point-based.

Moments due to its ability of representing global features have found in many application fields of image processing. Geometric moments are mainly used to capture global features of images. In [9–12], the watermark was embedded into moment-based normalized image against affine transformation. Xin et al. [13] embedded watermark by modifying magnitudes of pseudo-Zernike moments (PZMs) of an image. Zhang et al. [14] proposed a geometric invariant blind image watermarking by using invariant Tchebichef moments and independent component analysis (ICA). However, moment-based methods are highly vulnerable to cropping.

Histogram can measure the numerous global features of all pixels in an image, and the histogram distribution of an image is approximately invariant under geometric attacks. For this reason, some histogram-based watermarking schemes have been presented for the purpose of robust watermarking. Xiang et al. [15] developed an invariant image watermarking by using histogram shape and mean in the Gaussian filtered low-frequency component of images. Coltuc and Bolon [16] utilized exact histogram specification to mark images. This method is based on the connection between the statistical model of the images and the lattice structure assumed by discrete images. Chareyron et al. [17] extended the histogram specification method to chromatic histograms, and then to color histograms. Lin et al. [18] presented a blind watermarking algorithm based on the three-dimensional color histogram to resist geometric attacks and common image processing operations. The major limitation of this class is the incapacity to resist to local transformations.

The third sub-category uses the feature points to form local regions for embedding and extracting watermark. Bas et al. [19] utilized Harris corner points as the feature points. Tang and Hang [20] presented a method of combining feature extraction and image normalization to resist geometric attacks. In [21], feature points were extracted through Harris-Laplace detector. For a chosen feature points, a circular local region is formed and used for embedding and detection. In [22,23], elliptical local regions were constructed by Harris-Affine detector and elliptical watermark were spatially embedded in the corresponding local regions. In [24,25], normalized affine covariance regions were adopted to embed watermarks.

Although it has been proven that the feature point-based watermarking schemes are better than others in terms of robustness, there are still some drawbacks indwelling in the current feature point-based schemes. First, the feature point extraction techniques adopted by the current feature point-based methods, such as Harris detector or Mexican hat wavelet filtering, are sensitive to image modification. Second, most of these schemes directly embed watermarks in the spatial domain, which reduce the achievable robustness. Third, the interpolation error and the shift problem caused by geometric attacks limit the performance of watermarking system.

As an effective way to solve the above problems, Deng et al. [26] developed a robust watermarking method combining the local circular regions (LCRs) and Tchebichef moments. LCRs are formed by Harris-Laplace detector, and Tchebichef moments are employed to capture the global characteristics of the LCRs. To further reduce the computational complexity and exploit the statistical characteristics which are independent of the position of pixels in the image plane, we propose a geometrically resistant image watermarking approach by using local histogram in this paper. First, The LCRs are extracted by Harris-Laplace detector. Since the radius of each of LCRs is in direct proportion to its corresponding characteristic scale, these LCRs are covariant to scaling. But it is worth notice that these LCRs are overlapped seriously to each other, and directly embedding watermarks in these LCRs will decrease the robustness of the proposed watermarking system. Therefore, it is essential to selecting a set of stable and non-overlapped LCRs. Here, we develop a feature selection process based on graph theoretical clustering algorithm to choose a set of non-overlapped LCRs which inherently is invariant to scaling, translation, and projective transformation. Second, in order to resist to rotation, we need to determine the dominant orientation for each of chosen LCRs by calculating the dominant gradient orientation and normalize its dominant orientation. Third, due to their property to be independent of the position of pixels, the histogram shape and the mean of LCRs are applied for watermarking to overcome the interpolation error and the shift problem during geometric attacks. On the detection end, we adopt two kinds of local search strategies to further compensate the synchronization error caused by geometric attacks. Consequently, the robustness to geometric attacks and common image processing operations can be improved significantly through embedding the watermark in the local histogram shape. Extensive experimental results demonstrate that the proposed scheme outperforms the existing representative works in terms of robustness.

This paper is organized as follows. Section 2 describes the robust feature extraction, feature selection and local histogram computation. Section 3 presents the proposed watermarking scheme. Section 4 evaluates the watermarking scheme in terms of imperceptibility and robustness. Section 5 summarizes the conclusion.

2. Robust feature extraction and local histogram

2.1. Robust feature extraction

It has been proven that Harris-Laplace detector is invariant to image rotation, scaling, translation, partial
illumination changes, and projective transformation [27]. Compared with scale-invariant feature transform (SIFT), Harris-Laplace detector is more robust under scaling. So, we adopt the Harris-Laplace detector to extract feature points in the proposed scheme.

Harris-Laplace detector is the improvement of Harris detector. To obtain the invariance to scale changes, this detector first calculates a set of images represented at different resolution levels for reliable Harris detector. It then selects feature points with an automatic scale selection procedure. For Harris-Laplace detector, the scale-normalized second order moment matrix is defined as

$$m(X, \sigma_1, \sigma_D) = \sigma_D^2 g(\sigma_1) \otimes \begin{bmatrix} L_x^2(X, \sigma_D) & L_xL_y(X, \sigma_D) \\ L_xL_y(X, \sigma_D) & L_y^2(X, \sigma_D) \end{bmatrix},$$

(1)

where $\sigma_1$ is the integration scale, $\sigma_D$ is the differentiation scale, $L$ is the derivative computed in the $s$ direction, and $\otimes$ denotes the convolution operator over $X \in \mathbb{R}^2$. The scale-space representation is a set of images represented at different levels of resolutions. Given the $\sigma_D$, the uniform Gaussian scale-space representation $L$ is

$$L(X, \sigma_D) = g(X, \sigma_D) \otimes f(X),$$

(2)

where $g(X, \sigma_D)$ is the uniform Gaussian kernel with standard deviation $\sigma_D$ and mean zero, $f$ is an image, and $\otimes$ is convolution operator.

Given $\sigma_1$ and $\sigma_D$, the strength measure of this detector can be computed as

$$m(X, \sigma_1, \sigma_D) = \text{det}(m(X, \sigma_1, \sigma_D)) = \kappa \text{trace}^2(m(X, \sigma_1, \sigma_D)).$$

(3)

where $\kappa$ is a predefined constant. At each level of the scale space, the local maxima of the strength measure are regarded as the feature points.

The idea of automatic scale selection is to select the characteristic scale of a local structure, for which a given function attains an extremum over scales. In [28], normalized Laplacian-of-Gaussian (LoG) operator is used for finding the characteristic scale. The LoG is defined as

$$|\text{LoG}(X, \sigma_1)| = \sigma_D^2 |L_{xx}(X, \sigma_1) + L_{yy}(X, \sigma_1)|,$$

(4)

where $L_{xx}$ and $L_{yy}$ are second partial derivatives with respect to $x$ and $y$, respectively.

For each candidate point, an iterative algorithm is applied for detecting the location and the scale of feature points. The extrema over scale of the LoG are used to select the scale of feature points. Given an initial point $X$ with scale $\sigma_1$, the iteration steps are:

Step 1: Find the local extremum over scale of the LoG for the point $X_k$; otherwise, reject the point. The investigated range of scales is limited to $\sigma_l^{(k+1)} = t \sigma_l^{(k)}$ with $t \in [0.7, \ldots, 1.4]$.

Step 2: Detect the spatial location $X_{k+1}$ of a maximum of the strength measure nearest to $X_k$ for selected $\sigma_l^{(k+1)}$.

Step 3: Go to Step 1 if $\sigma_l^{(k+1)} \neq \sigma_l^{(k)}$ or $X_{k+1} \neq X_k$.

2.2. Feature selection

Since feature points can only provide position information, the neighborhood of the points are required for watermark embedding and detection. For each feature point, a LCR can be formed. The radius of the LCR is

$$r = \tau \cdot |\sigma|,$$

(5)

where $|\cdot|$ is rounding operation, $\sigma$ is the characteristic scale, and $\tau$ is a positive integer, which is used to adjust the size of a LCR. A large value of $\tau$ will increase the capacity of watermarking system. However, the system robustness will be decreased with the increase of $\tau$. So, there is a compromise between the capacity and the robustness.

In order to improve the robustness of the proposed scheme, appropriate LCRs should be selected. Usually, features points with small scales have a low repeatability. While, feature points with large scales have also a low repeatability. Moreover, the LCRs centered at these feature points with large scales will seriously overlap with each other. As a consequence, feature points with scale below 5 or above 10 will be ignored [24].

Furthermore, the distance of feature points must be considered carefully. If the distance is small, LCRs will overlap in large areas, and if the distance is large, the number of LCRs will be insufficient. So, a distance constraint $D$ is adopted to control the distribution of LCRs. In this proposed scheme, we utilize minimum spanning tree (MST) clustering algorithm [29] to group these feature points according to the distance constraint $D$. In other words, feature points whose adjacent distance is less than $D$ will be assigned into a cluster. To the same cluster, feature points whose strength is the largest are used to form LCRs. Moreover, distance constraint $D$ can also be treated as a secret parameter to enhance the security of the proposed scheme.

After the above steps, a set of non-overlapped LCRs are chosen appropriately. Fig. 1 illustrates the final selected LCRs for Baboon, Lena, and Peppers images. Over these non-overlapped LCRs, local histograms are computed and used for watermark embedding and detection.

2.3. Local histogram computation

In the image processing context, the histogram of an image is a graph showing the number of pixels in the image at each different intensity value. The histogram with equal-sized bins may be described as

$$H = \{h_i(i) | i = 1, \ldots, L_h\},$$

(6)

where $H$ is a vector denoting the gray-level histogram of an image $F = \{f(x, y) | x = 1, \ldots, R, y = 1, \ldots, C\}$, and $h_i(i)$ represents the number of pixels in the $i$th bin and satisfies $\sum_{i=1}^{L_h} h_i(i) = R \times C$. Suppose that the bit depth of an image is $P$ bits. The relationship between the number of
bin \( L_h \) and the bin width \( M \) is given by
\[
L_h = \begin{cases} 
2^p / M & \text{if } \text{mod}(2^p / M) = 0 \\
\left\lfloor 2^p / M \right\rfloor + 1 & \text{otherwise}
\end{cases}
\] (7)
where \( \lfloor \cdot \rfloor \) is the floor operation.

The mean of an image is calculated as
\[
\mu = \frac{1}{RC} \sum_{x=1}^{R} \sum_{y=1}^{C} f(x, y).
\] (8)

It has been proven that the histogram shape and mean are invariant to rotation, scaling, and translation due to their statistical independence to the pixel position [30]. In our scheme, we compute the histogram shape and mean in the LCRs. By combining the stable LCRs with the independence of the histogram and the mean to the pixel position, the robustness to geometric attacks can be improved.

3. Proposed watermarking scheme

For the feature point-based watermarking schemes, the watermark synchronization error can be solved by binding watermarking with local feature regions. That means these local feature regions must be high repeatability between the original and attacked image. In the proposed scheme, we extract LCRs with Harris-Laplace detector described in Section 2. After feature selection and dominant orientation normalization, a set of invariant LCRs can be generated. Considering the statistical independence of the histogram and the mean to the pixel position, the watermark embedding and detection are conducted based on the histogram in the LCR.

3.1. Watermark embedding

Let \( F = \{ f(x, y) \mid 1 \leq x \leq R, 1 \leq y \leq C \} \) be the original gray-level image. The watermark generated by the secret key \( K \) is denoted by \( W = \{ w_i \mid i = 1, 2, \ldots, L_w \} \), where \( w_i \in \{0, 1\} \) and \( L_w \) is the watermark length. Fig. 2 shows the watermark embedding process, and the detailed steps are given as follows:

Step 1: To extract LCRs, we adopt Harris-Laplace detector, as explained in Section 2. These LCRs are...
overlapped seriously each other. For the purpose of enhance the robustness of our scheme, the watermarks should be embedded in a set of stable and non-overlapped LCRs. In this respect, we use the MST-based graph theoretical clustering algorithm to obtain the set of non-overlapped LCRs.

Step 2: The LCRs extracted by Harris-Laplace detector are inherently robust to common image processing operations, scaling, translation, affine transformation, and random bending attacks (RBAs). For each of the chosen LCRs, we calculate the gradient direction of all pixels within the LCR by using first order derivative, and the peak of the gradient histogram is assigned as the dominant orientation of the LCR. By normalizing the dominant orientation, we can achieve the invariance to rotation. Thus, the set of selected LCRs are resilient to common image processing operations and geometric attacks.

However, it is very hard to directly implement the above operations on the LCRs. So, we use zero padding to solve this problem. The LCRs are mapped to the patches with size $(2r+1) \times (2r+1)$ by using zero padding.

Step 3: To eliminate the interpolation error and the shift problem induced by geometric attacks, we compute the histogram and the mean of LCRs, then embed watermark in the histogram bins.

For a chosen LCR, the average value is calculated as $\bar{X}$. An embedding range $B = \{1 - \lambda \bar{X}, (1 + \lambda \bar{X})\}$ is determined, where $\lambda \in [0.4, 0.7]$ is a positive number to adjust the histogram width. In our experiments, $\lambda$ is set to 0.6. The histogram vector $H$ is produced which has $L_w$ equal-sized bins of width $M$. In order to embed all bins, $L_w$ should not be less than $2L_w$.

When embedding watermark, we first analyze the relative relationship between groups of two neighboring bins. Obviously, the number of pixels in the bin has essential effect on the relative relationship. In some bins, the number is less (zero or a few), which is defined as bad bins. The relative relationships involving the bad bins are unstable and then affect the watermark embedding even if the number of pixels in these bins is only modified slightly. Although the embedding range $B$ can be beneficial to lower the number of the bad bins, the problem has not been solved completely. Especially, the effect produced by the bad bins is more apparent in the LCRs. In practice, we introduce a threshold to further remove the bad bins in the embedding range $B$ to guarantee embedding watermark in LCRs.

Step 4: Let $\text{BIN}_1$ and $\text{BIN}_2$ be two consecutive bins in the extracted histogram. The number of pixels in these two bins are $a$ and $b$, respectively. The embedding rules is described as

$$\begin{align*}
\begin{cases}
a/b \geq T & \text{if } w(i) = 1 \\
b/a \geq T & \text{if } w(i) = 0
\end{cases}
\end{align*}$$

where $T$ is a threshold controlling the number of modified pixels. Obviously, the $T$ value directly impact on the imperceptibility of the watermark.

Fig. 3 shows the procedure of embedding one-bit watermark in two consecutive bins. If $w(i)$ is “1” and $a/b \geq T$, no operation is needed. Otherwise, if $w(i)$ is “1” and $a/b < T$, randomly selected $l_w$ pixels from $\text{BIN}_2$ will be modified to $\text{BIN}_1$, satisfying $a_1/b_1 \geq T$. When $w(i)$ is “0” and $b/a < T$, randomly selected $l_w$ pixels from $\text{BIN}_1$ will be moved to $\text{BIN}_2$, achieving $b_2/a_2 \geq T$. The rule for modifying these selected pixels is formulated as

$$\begin{align*}
\begin{cases}
f_1(i) &= f_1(i) + M, & 1 \leq i \leq l_0 \\
f_2(j) &= f_2(j) - M, & 1 \leq j \leq l_1
\end{cases}
\end{align*}$$

where $f_1(i)$ is the $i$th selected pixel in $\text{BIN}_1$ and $f_2(j)$ is the $j$th selected pixel in $\text{BIN}_2$. The modified pixels $f_1(i)$ and $f_2(j)$ belong to $\text{BIN}_2$ and $\text{BIN}_1$, respectively. $l_0$ and $l_1$ can be computed as

$$\begin{align*}
l_0 &= (Tb-a)/T, \\
l_1 &= (Ta-b)/T.
\end{align*}$$

By repeating the above procedure, the $L_w$-bits watermark can be embedded in the LCR. After the zero-removing and inverse orientation normalization, the watermarked LCR can be obtained. When we replace the original chosen LCRs with the watermarked LCRs, the watermarked image can be obtained.

3.2. Watermark detection

Similarly to watermark embedding, the first step in watermark detection is extracting the LCRs by Harris-Laplace detector. The watermark is then retrieved from the LCRs. The ownership can be proven successfully if the watermark is detected correctly from at least one LCR. In detail,

Step 1: Harris-Laplace detector is used to extract feature points and form LCRs. According to the similar feature selection procedure, a set of non-overlapped LCRs can be obtained. This feature selection procedure can redetect those LCRs that have been embedded watermark with very high probability.

Step 2: The peaks of the gradient histogram within the LCRs are assigned as the dominant orientation of LCRs. Through orientation normalization, the rotation invariance of the selected LCRs can be achieved. In the implementation, zero padding is required to map the LCRs into the patches with the size of $(2r+1) \times (2r+1)$.

Step 3: For each of the chosen LCR, computing the mean $\bar{X}$ and generating the histogram vector $H$ with $L_w$ equal-sized bins of width $M$ from the embedding range $B = \{1 - \lambda \bar{X}, (1 + \lambda \bar{X})\}$. As in the process of watermark embedding, bad bins are excluded by integrating the embedding range $B$ with the same threshold.

Step 4: In order to extract watermark bit, we divide two neighboring bins as a group. Suppose that the number of the pixels in two consecutive bins are $a$ and $b$, respectively. One-bit watermark can be extracted by referring the following equation:

$$w(i) = \begin{cases} 1 & \text{if } a/b \geq 1 \\
0 & \text{otherwise}
\end{cases}$$

By repeating the above process, all watermark bits can be extracted and the estimated watermark sequence is described as $W = \{w(i) | i=1, 2, \ldots, L_w\}$. The extracted watermark sequence is then compared with the original embedded watermark to decide success detection.
Two kinds of errors are possible in the watermark detector: false-positive error probability (no watermark embedded but detected having one) and false-negative error probability (watermark embedded but detected having none). Typically, there are two optimization criterions in selecting the detector parameters. One is the minimum error probability criterion which aims to minimize the total error probabilities. However, this criterion could overestimate the detection threshold and then increase the false-negative error probability. The other is Neyman–Pearson criterion, which could minimize the false-negative error probability under a fixed false-positive error probability. Therefore, in the existing feature points-based watermarking scheme, it is usual to determine the detection threshold based on a fixed false-positive error probability [31]. Since it is rather difficult to have exact probabilistic models of these two kinds of errors, we adopt a simplified model in choosing the detector parameters as below.

For an un-watermarked image, the extracted bits are treated as independent random variables with probability 0.5. According to Bernoulli trials, the false-positive probability of an LCR is

$$P_{FP_{LCR}} = \sum_{i=I_{TD}}^{L_{W}} (0.5)^i \frac{L_{W}!}{i!(L_{W}-i)!}.$$  

(13)

where $I_{TD}$ is the predefined threshold, $i$ is the number of the matching bits and $L_{W}$ is the length of the watermark sequence. Furthermore, when an image is claimed to be watermarked if at least two regions are detected, the false-positive probability of one image can be expressed as

$$P_{FP_{Image}} = \sum_{j=2}^{N} \binom{N}{j} (P_{FP_{LCR}})^j (1-P_{FP_{LCR}})^{N-j},$$  

(14)

where $N$ is the total number of LCRs in an image.

4. Experimental results and analysis

This section reports on the performance of the proposed watermarking scheme. The watermark imperceptibility and robustness are evaluated by using 50
different $512 \times 512$ grayscale images which includes four benchmark images Baboon, Lena, Peppers, and Plane.

In the experiments, a 20-bits pseudorandom bipolar sequence used as the watermark is embedded into the 40 histogram bins. The threshold $T$ in Eq. (9) is set to 2. When $T_D=17$ and $N=20$, the false-positive probability is $P_{FP_{Image}} = 3.1 \times 10^{-4}$.

4.1. Imperceptibility test

Fig. 4 shows the original images, the watermarked versions and the amplified magnitudes of the watermarks in Lena and Peppers. We can see that the watermarked images are perceptibly similar to the original images. For all the 50 test images, the average PSNR values between the original images and the watermarked images are greater than 55 dB.

4.2. Robustness test

Stirmark 4.0 [32] are used to generate 22 typical attacks to examine the robustness of the proposed watermarking scheme. These attacks consist of 8 common image processing operations and 14 geometric attacks.

The watermark detection results with respect to common image processing operations are shown in Table 1 for four benchmark images, respectively. Table 2 gives the results of robustness against geometric attacks. Furthermore, in order to demonstrate the superiority of our method, we compare it with other two representative methods [21,26], both of which extracted LCRs with Harris-Laplace detector. The values in main table units indicate the ratio of the number of LCRs where watermarks are successfully detected from attacked images to the number of original watermarked LCRs.

In watermark detection end, since the Harris-Laplace detector cannot provide sufficiently high accuracy, local search is necessary to compensate for synchronization errors induced by geometric attacks. To address this problem, we construct two local search spaces:

- **The position-based search**: In the detection procedure, we extract the watermark by changing the position of each LCR in the amount of $\pm 2$ pixel. In other words, if the difference between LCRs from original images and those from attacked images is below 2 pixels, we regard the LCRs as being redetected correctly.

- **The mean value-based search**: the local search space $S = [\bar{A}(1-|A_1|), \bar{A}(1+|A_2|)]$ is formed according to the percentages of the estimated maximum proportional deviation of the mean due to various attacks. The parameters $A_1$ and $A_2$ are assigned as $-5\%$ and $+5\%$.

As shown in Tables 1 and 2, the newly proposed scheme outperforms the schemes of Seo and Yoo [21] and Deng [26]. Among these three existing schemes, the scheme of Seo and Yoo [21] shows the worst performance. Although this method spatially embedded the circular watermark pattern in the circular patches extracted by Harris-Laplace detector, the interpolation error and shift problem during geometric attacks have not been effectively resolved. Due to employing two kinds of local search strategies to further compensate the synchronization error induced by geometric attacks, the new proposed scheme shows better performance than our previous work [26]. However, the main drawback in the proposed scheme is that the effective watermark embedding capacity is lower. Hence, in the future work, one consideration is to seek a new way [33] enhancing the capacity of the watermarking scheme. Moreover, using
more robust image watermarking schemes for large-scale visual information secure retrieval and management will be another consideration we will focus on [34,35].

5. Conclusion

In this paper, we develop a geometrically robust image watermarking scheme by integrating LCRs with histogram. The Harris-Laplace detector is first utilized to extract feature points and form LCRs which inherently is invariant to many attacks, such as scaling, translation and projection transformation. Then, a MST-based feature selection procedure is introduced to guarantee the watermark being embedded in a set of non-overlapped LCRs. For each selected LCR, dominant orientation normalization is conducted to enhance the resistance to rotation. Finally, considering the interpolation error and the shift problem induced by various attacks, we compute the histogram and mean over these chosen LCRs and implement the watermark embedding by modifying the shape of local histogram. Experimental results confirm that the new proposed scheme outperforms other representative methods in terms of robustness to geometric attacks and common image processing operations.

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