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Robust Reversible Watermarking via clustering and Enhanced pixel Wise Masking

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Abstract: *Digital watermarking technique have been indicated so far as a possible solution when, in a specific scenario like authentication, copy right protection, fingerprint etc. There is the need to embed an informative message in a digital document in an imperceptible way. Such a goal is achieved by performing Robust reversible watermarking (RRW) methods. However conventional RRW methods are not readily applicable in practice. This is mainly because:1)they fail to offer satisfactory reversibility on large scale image database;2)they have limited robustness in extracting watermarks from the watermarked images destroyed by unintentional attacks; and 3) some of them suffer from extremely poor invisibility for watermarked image. Therefore it is necessary to have a framework that overcome these three problems. To overcome these drawbacks, wavelet-domain statistical quantity histogram shifting and clustering (WSQH-SC). Compared to conventional methods, this method improves robustness and reducing run-time complexity by using histogram shifting and clustering. Additionally WSQH-SC includes the PIPA to effectively handle overflow and underflow of pixels. Furthermore, to increase its practical applicability, WSQH-SC methods designs an enhanced pixel-wise masking to balance robustness and invisibility. We perform more experiments over natural, medical, medical, and synthetic aperture radar images to show the effectiveness of WSQH-SC by comparing with the conventional methods*

Keywords: *Integer wavelet transformation, K-means clustering, making ,robust reversible watermarking*

I. Introduction

Image watermarking is finding more and more support as a possible solution for protecting intellectual property rights. To aim this, many techniques have been proposed in literature in last few years. Among those Robust reversible watermarking has found a huge surge of experimentation in its domain in past decade as a need of recovering the original image after extracting the watermark arises in various applications like the law enforcement, medical and military image system. Multimedia data embedding or digital watermarking refers to the process of inserting the information bits into the host multimedia signal without introducing perceptible artifacts[1]-[2]. A variety of embedding techniques, ranging from high capacity bit modification to low capacity bit modification to transform domain methods, are used in various applications such as authentication, meta-data tagging ,content-protection and secret communication. Most multimedia data embedding techniques modify and hence, distort the host signal in order to insert the additional information p[2]-[3].

Although researchers proposed some RW methods for various media, e.g., images , audios , videos , and 3-D meshes[4] , they assume the transmission channel as lossless. The robust RW (RRW) is thus a challenging task. For Robust RW, the essential objective is to accomplish watermark embedding and extraction in both lossless and lossy environment[5]. As a result, RRW is required not only recover host images and watermarks without distortion for the lossless channel, but also resist unintentional attacks and extract as many watermarks as possible for the noised channel . Recently, RRW methods for digital images have been proposed , which can be divided into two groups: Histogram rotation (HR)-based methods and histogram distribution constrained (HDC) methods[6]. The HR based methods, accomplish robust lossless embedding by slightly rotating the centroid vectors of two random zones in the non overlapping blocks[7]. Due to the close correlation of neighboring pixels, these methods were stated to be robust against JPEG compression. However they are sensitive to "salt-and-pepper" noise, it leads to poor visual quality of watermarked images, and impedes lossless recovery of original (host) images and watermarks. To overcome this problem, the HDC methods have been developed in spatial and wavelet-domains, which divide image blocks into different types and embed the modulated watermarks for each type based on histogram distribution. Unfortunately, these conventional methods suffer from unstable reversibility and robustness. In summary, the above analysis shows that both kinds of methods are not readily applicable in practice[8]. Therefore, a novel pragmatic RRW framework with the following three objectives: 1) Reversibility, 2) Robustness and 3) Invisibility.

II. Related work

A. GSQH Driven Method

The histogram plays an important role in many practical models and applications, e.g., histogram of oriented gradient features , bag-of-words , and digital watermarking . For RW methods, SQH has recently received considerable attention due to stability and simplicity, e.g., arithmetic average of difference (AAD) histogram, difference histogram, and prediction error histogram. In particular, we proposed a GSQH driven method, which embeds and extracts watermarks by SQH shifting. The following is a brief review of this method.

Given a t-bit host image I with n non overlapping blocks, its SQH can be generated by calculating the AAD of each block. For convenience, we denote the SQH by a set of data pairs, i.e., X = {(x1, n1) , . . . , (xi , ni) , . . . , (xm , nm)},
where xi represents the different values of the AAD, and ni is the corresponding frequency of xi in SQH. Let xr and xl be the two peak points of SQH, wherein

r = arg max n_i, 1≤ i≤ m^* (1)

and

l = arg max $n_{i,}$ 1≤ i ≤ m^* , i≠ r (2)

suppose $x_1 \leq x_r$then the embedding is done according to

$$s_k^w = \begin{cases} s_k - z - 1, & if\ s_k < x_1 - z \\ s_k - b_k(z+1), if\ x_1 - z \leq s_k \leq x_1 \\ 0, & if\ x_1 \leq s_k \leq s_r \\ s_k + b_k(z+1),\ if x_r \leq s_k \leq x_r + z \\ s_k + z + 1 & if s_k \leq x_r + z \end{cases}$$

in which s^k and s_k^w are the AADs of the kth block in the host and watermarked image respectively,b_k ϵ $\{0, 1\}$ is the k th watermark bit, and z≥ 0 is a scale factor. Extensive experimental results suggest that the GSQH driven method has its pros and cons. On one hand, it combines GSQH and histogram shifting together to obtain good performance. On the other hand, however, it has three shortcomings: 1) it uses the AADs of all of the blocks, both reliable and unreliable, to generate the SQH of the host image, which increases complexity of watermark embedding; 2) it fails to consider the optimization of watermark strength; and 3) it suffers from unstable robustness against JPEG compression. By taking these pros and cons into account, we therefore integrate PIPA, SQH shifting, clustering, and EPWM into a novel RRW framework, which effectively overcomes the above shortcomings and makes our work intrinsically different from existing RRW methods.

B. PWM

The past years have witnessed the significance of HVS in various applications and many visual masking algorithms revealing the perceptual characteristics of HVS have been applied to digital watermarking . In particular a PWM algorithm proposed by Barni et al . has received much publicity, which computes the JND threshold of each wavelet coefficient based on resolution, brightness, and texture sensitivity. Given the wavelet coefficient $c_p^w(i,j) at\ (i,j)$ in the sub-band c_p^w with resolution level $\rho\ \epsilon\ \{0,1,2,3\}$ and orientation

ῳ ϵ $\{LL, LH, HL, HH\}$,the JND threshold is denoted by

$$JND_p^w(i,j) = \Theta(\rho, ῳ)\varphi(\rho,i,j)\pi(\rho,i,j)^{0.02}$$

here ,Θ(ρ,ῳ),φ(ρ,i,j) and π(ρ,i,j) evaluate resolution, brightness, and texture sensitivities respectively.
In summary ,PWM estimates how HVS perceives disturbances in images by considering the resolution, brightness and texture sensitive .However, it is not precise enough because the low pass sub-band at the forth resolution level ,i.e c_3^{LL} has less image content, which ends up with the approximate estimation of texture and brightness. To solve this problem, we design the EPWM to better depict local sensitivity of HVS, which not only improves texture and brightness sensitivities but also optimizes the sensitivity adjust watermark strength, which is helpful for increasing practical applicability of the proposed algorithm.

III. Proposed Framework

We introduce a new RRW framework, i.e., WSQH-SC, which accomplishes the robust lossless embedding task by incorporating the merits of SQH shifting, k-means clustering and EPWM. WSQH-SC comprises two processes: watermark embedding and extraction. In view of their similarity, the embedding process in which the three modules are termed: 1) PIPA; 2) SQH construction; and 3) EPWM-based embedding, and they are detailed in the following three subsections. To be specific, WSQH-SC first investigates the wavelet sub-band properties in depth and exploits PIPA to preprocess the host image, which is of great importance to avoid both overflow and underflow of pixels during the embedding process. Afterward, the host image is decomposed by the 5/3 integer wavelet transform (IWT) [30] and the blocks of interest in the sub-band c_0^{HL} are selected to generate the SQH with the help of the threshold constraint. Finally, watermarks can be embedded into the selected blocks by histogram shifting, wherein EPWM is designed to adaptively control watermark strength. After the IWT reconstruction, the watermarked image is obtained.

3.1. PIPA:

In RRW, how to handle both overflow and underflow of pixels is important for reversibility. Xuan et al. proposed a pixel adjustment strategy to tackle this problem. Unfortunately, it cannot be directly applied to wavelet domain because the adjustment scale related to wavelet transform is unknown. As a consequence, we develop PIPA to handle this problem. Firstly, PIPA deeply exploits the intrinsic relationship between wavelet coefficient and pixel changes. Secondly, by taking the scale and region of wavelet coefficient changes into consideration, PIPA determines the adjustment scale and employs the pixel adjustment strategy to preprocess the host images. To better present the technical details of PIPA, Table III gives the 5/3 filter coefficients . Based on this, we investigate the effects of changing wavelet coefficients on pixels from two aspects.

3.1.1) Single Sub-Band and Single Wavelet Coefficient:

Given the watermark strength λ, we consider the changes of pixels when an arbitrary wavelet coefficient in C_0^w is changed. In particular, if $c_{i,j}^w \leftarrow c_{i,j}^w + \lambda$, the corresponding changes of pixels in terms of scale and region. wherein the affected region is represented by the location of the center, vL = [1, 2, 1] and vH = [1,2,−6, 2, 1]. we can derive three properties: 1) intra-band correlation, i.e., the pixel regions affected by the neighboring wavelet coefficients in a sub-band are overlapped; 2) inter-band correlation, i.e., the regions affected by the wavelet coefficients in different sub-bands are also overlapped; and 3) bi-directional change, i.e., the grayscale values of pixels affected by the wavelet coefficients in the $c_0^{HL}, C_0^{LH}\, and\; C_0^{HH}$ sub-bands are both increased and decreased. Based on this, we conclude that it is impractical to use all of the wavelet coefficients in a sub-band for watermark embedding. That is because it is virtually impossible to determine the adjustment scale and use the pixel adjustment strategy to solve both overflow and underflow problems. Inspired by , we aim to search for a new solution by further investigating the effects of changing wavelet coefficients on pixels based on multiple sub-bands and multiple wavelet coefficients.

3.1.2) Multiple Sub-Bands and Multiple Wavelet Coefficients:

Considering an arbitrary block with the top left corner at (p, q) in c_0^w , 1 ≤ p < M, 1 ≤ q < N, we investigate the changes of wavelet coefficients and pixels in two special cases,. Here, vF = [0, 0, 1, 0, 1, 0, . . . , 1, 0, 0]2×h−1, vG = [1, 2, . . . , 2, 1]2×w−3 and the affected region of pixels is denoted by the location of its top left corner. To further illustrate such effects, Fig. 2 shows an example in which the block size is 3 × 3, and the wavelet coefficients of two neighboring blocks in c_0^{LL} and c_0^{LH} are changed simultaneously., we can deduce that: 1) the affected pixel regions are non overlapped when the wavelet coefficients of neighboring blocks are changed at the same time and 2) the pixel changes are mono directional and the maximum change scale equals λ. In this case, we can easily determine the adjustment scale and use the pixel adjustment strategy to preprocess host images.

3.2.SQH Construction

In this subsection, to better resist unintentional attacks, we build a SQH (Statistical quantity Histogram) with a threshold constraint. Inspired by characteristics of the wavelet coefficients [12], we focus on mean of wavelet coefficients (MWC) histogram by taking the following two properties into account: 1) it is designed in highpass sub-bands of wavelet decomposition, to which HVS is less sensitive, leading to high invisibility of watermarked images and 2) it has zero mean. In particular, an MWC histogram is generated based on the following procedure.

Consider a given host image I, we first decompose I using 5/3 Integer Wavelet Transform (IWT) to obtain the sub-band c_0^{HL} into non overlapping blocks. Let S=$[S_1, \dots\dots\dots\dots, S_k, \dots\dots\dots\dots, S_n]$ be the MWCs in the sub-band then MWC of the kth block, S_K, is defined as

$$S_k = \frac{1}{(h-2)*(w-2)} \sum_{i=2}^{h-1} \sum_{j=2}^{w-1} P_k^{(i,j)} \qquad (7)$$

Where$P_k^{(i,j)}$represents the wavelet coefficient at (i,j) in the kth block. To construct the MWC histogram, our concern is the possibility of utilizing the blocks of interest in a sub band, which will be helpful for simplifying

the embedding procedure. In view of the histogram distribution of MWC, only the peak and its neighbors in the histogram are mostly useful for embedding. Therefore, a threshold constrained is applied to the blocks retain those of interest, each of which satisfies the following condition:
d$(x, s_k) \leq \delta$, $1 \leq k \leq n$

3.3. EPWM-Based Embedding

It has been well acknowledged that a balance between invisibility and robustness is important for robust watermarking methods. Although many efforts have been made to design lossless embedding models, little progress has been made in this trade-off. Therefore, we develop EPWM to tackle this problem by utilizing the JND thresholds of wavelet coefficients to optimize watermark strength. In view of the disadvantages of PWM , EPWM focuses on improving the local sensitivity of images to noise by mainly estimating brightness and texture sensitivities in a more precise way. Motivated by the benefits of luminance masking , we first redefine the brightness sensitivity by calculating the luminance masking of the low-pass sub-band at resolution level ρ.

3.3.1. Extraction Based on k-Means Clustering

If watermarked images are transmitted through an ideal channel, we can directly adopt the inverse operation of to recover host images and watermarks. However, in the real environment, degradation may be imposed on watermarked images due to unintentional attacks, e.g., lossy compression and random noise. Therefore, it is essential to find an effective watermark extraction algorithm so that it can resist unintentional attacks in the lossy environment. Based on the aforementioned embedding model in the MWC histogram of watermarked images are divided into three parts in which, the center part corresponds to watermark bit "0" and others to bit "1." To extract the embedded watermarks, the key issue is to partition these parts dynamically. In the lossy environment, this is very difficult because the histogram distribution of MWC is destroyed by unintentional attacks, . In this paper, by investigating the effects of unintentional attacks on histogram, we treat the partition as a clustering problem with a certain number of clusters and adopt the k-means clustering algorithm to tackle this problem for simplicity. Similar to the embedding process, we first decompose the watermarked image with 5/3 IWT and construct the MWC histogram by calculating the MWCs of blocks of interest in the sub-band . Let $s^w = [s_1^w \dots\dots\dots\dots\dots\dots.. s_m^w]$be the obtained MWCs, F = { f1, . . . , fμ} be the cluster centers, and g ={g1, . . . , gμ} be the set of clusters, wherein μ is the number of clusters. Particularly, the initial cluster centers are given by considering the features of the embedding process, e.g., F = {τ min (Sw) , 0, τ max (Sw)} for μ = 3, to improve the efficiency of classification.

Embedding Procedure Of The Proposed Framework

Input: A t-bit host image I with the size of 2M × 2N, a watermark sequence b = [b1, . . . , bm], and block size h × w.

Output: The watermarked image I^w.

1. Apply PIPA to host image I to obtain the adjusted image I', and
record the locations of the pixels changed by PIPA;
2. Decompose I' using 5/3 IWT and divide the sub-band c_0^{HL} into n
non overlapping blocks with the size of h × w;
3. Compute the MWCs of all of the blocks with (5) and obtain
S = $[S_1, S_2, \dots\dots\dots\dots\dots, S_m]$;
4. Retain blocks of interest with the threshold constraint in (6) and construct SQH;
5. Perform EPWM to compute the watermark strength

$$⋋= \frac{a}{M * N} \sum_{i-1}^{M} \sum_{j-1}^{N} JND_{\rho}^{\dot{\omega}}(i,j)$$

6. **For** k = 1 to m do
7. Embed the kth watermark bit b_k with $s_k^w = s_k +$ ⍰⍰b_k
8. **End for**
9. Reconstruct the watermarked image Iw with inverse 5/3 IWT.

Extraction Procedure Of The Proposed Framework

Input: A watermarked image I^w with the size of 2M × 2N, block size h × w, watermark strength λ and the locations of the pixels changed by PIPA.

Output: The recovered watermark sequence b^r and image I^r .

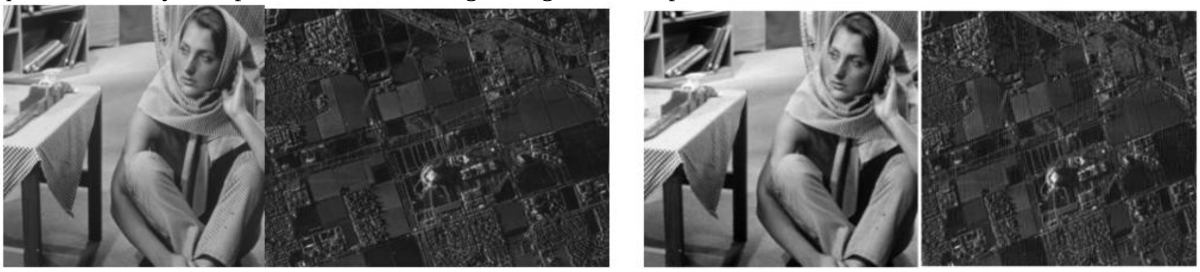
1. Decompose I^W using 5/3 IWT and divide the sub-band c_0^{HL} into n non overlapping blocks with the size of h × w;
2. Compute MWCs of blocks of interest with (5) and obtain
$S^W = [S_1^W, \dots \dots \dots, S_k^W, \dots \dots \dots \dots . S_m^W]$
3. Classify Sw with k-means clustering;
4. **For** k = 1 to m do
5. Extract the embedded watermarks

$$b_k^r = \begin{cases} 0, & if\, s_k^w \epsilon\ class\ II \\ 1, & if\, s_k^w \epsilon\ classI\ or\ class\ II \end{cases} for\ \mu = 3$$

6.Recover the embedded watermarks
7.**end for**
8.Perform inverse IWT followed by PIPA to obtain the recovered image I^r.

IV. Experimental Results

The proposed algorithm is applied on various images like natural, medical and aerial images. The qualitative analysis is performed on the image using statistical parameters.



(a) (b) c) (d)

Figure 1. (a) Original Lena Image (b) Original SAR Image (c)&(d) Watermarked Images

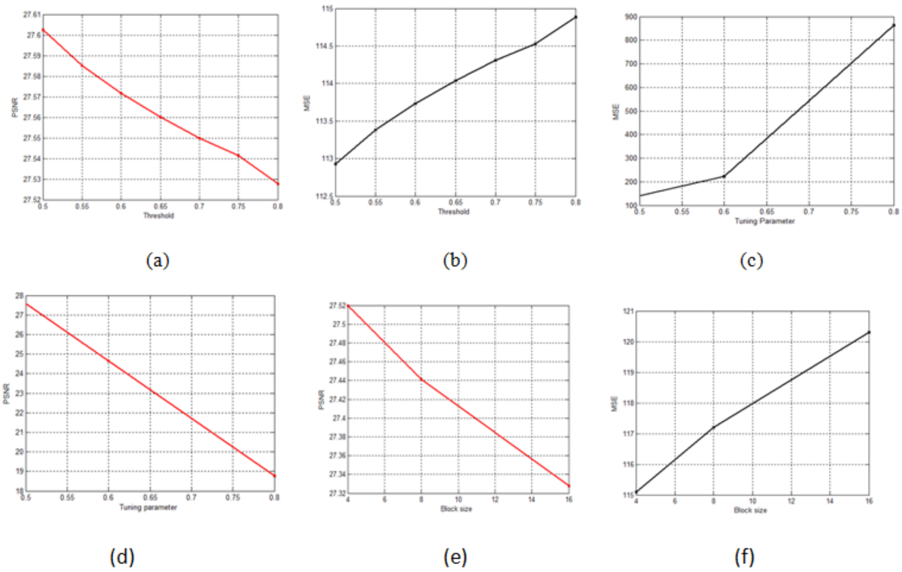


FIGURE2: (a)performance analysis for proposed algorithm (b) MSE variations for proposed algorithm (c)&(d) Variation of PSNR and MSE for different tuning parameters(e)&(f)PSNR and MSE variation for different blocksizes

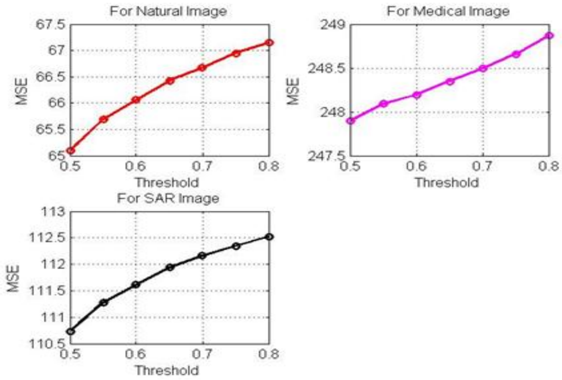


Figure 6. Overall Performance of the proposed methods for different images with varying thresholds

V. Conclusion

In this paper, we have developed a novel framework for reversible watermarking. It includes carefully designed PIPA, SQH shifting and clustering, and EPWM, each of which handles a specific problem in RRW. PIPA preprocesses host images by adjusting the pixels into a reliable range for satisfactory reversibility. SQH shifting and clustering constructs new watermark embedding and extraction processes for good robustness and low run-time complexity.

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