OPTIMAL RATE ALLOCATION FOR LOGO WATERMARKING

Yuanwei Lao and Yuan F. Zheng

Dept. of Electrical and Computer Engineering
The Ohio State University, Columbus, Ohio 43210
Email: {laoy,zheng}@ece.osu.edu

ABSTRACT

We consider the joint application of Human Vision System and rate allocation theory in logo watermarking. A new algorithm is proposed under this framework, in which the logo is multi-level decomposed, compressed and embedded into the decomposed host with the energy of the compressed logo optimally distributed across different subbands of the host. The scheme is verified to be robust against general signal attacks, and experimental comparison shows its superiority to other approaches. Moreover it is quite suitable for hardware implementations by using reversible wavelet transform.

***Index Terms*—** Watermark, RWT, HVS, rate allocation

1. INTRODUCTION

In copyright protection, digital watermarking [1] has become one of the most promising technologies to prevent intellectual properties from unauthorized uses. *Logo watermarking*, in contrast to conventional sequence watermarking, is visually more meaningful and thus has more practical applications. The major advantage is that the natural adaptive filtering ability of human perception could help recognize the extracted logo for ownership identification instantaneously, which is not possible to use empirical thresholds in the approaches of sequence watermark detection.

Many types of algorithms have been proposed for this purpose. Those based on Discrete Wavelet Transform (DWT) have gained advantages over other transform or spatial techniques due to their high robustness and spatial locality advantages. Niu et al [2] converted the logo into bit-planes and embedded them into different subbands of DWT decomposed host image. Kundur and Hatzinakos [3] did a milestone work for logo watermarking, which embedded one-level DWT decomposed logo into multi-level decomposed host image based on a Human Vision System (HVS) model by calculating a perceptual index, called "Salience". Reddy and Chatterji [4] extended Barni et al's results [5] for logo watermarking, which applied the idea of perceptual weights from [6].

In all previous works, compression of the logo as an image was not a primary consideration. We argue that for logo watermarking, the logo has to be compressed to minimize the impact to the quality of the host since a visually meaningful logo usually contains a large amount of data. Furthermore, the compression mechanism should not cause too much distortion to the logo in order for the extracted logo to be easily recognizable, which unfortunately affects the quality of the host image in an adverse way since a less distorted logo needs more data. As a result, a tradeoff between the distortion of the host and that of the logo has to be made, which should ideally be optimal such that given the limitation to the distortion of the host, the distortion to the logo is minimal. In this paper, we describe a new logo watermarking algorithm which optimizes such a tradeoff.

The algorithm makes use of the reversible wavelet transform (RWT) [8], a transformative DWT, to decompose both logo and host images into multiple subbands and then embeds the coefficients of each subband of the logo into the corresponding subband of the host. In the embedding process, the algorithm allocates energy to each subband of the logo optimally by minimizing the distortion of the logo subject to the constraint imposed on the level of distortion of the host. While formulating the distortion of the host, a well-known HVS model is utilized to automatically identify the most imperceptible areas of the host for embedding. In addition, statistical distribution of the coefficients of each logo subband is considered as a factor to the distortion of the corresponding subband of the host. By doing all the above, we obtain a new logo embedding algorithm which can guarantee the distortion level of the host while the distortion of the logo is minimized. The new algorithm is also robust to various types of attacks, and the extracted logo maintains the most fidelity in comparison with other approaches.

In Section 2, we briefly introduce the new logo watermarking scheme. Theoretical derivation is presented in Section 3. Experimental results are given in Section 4, and Section 5 concludes this paper.

2. PROPOSED LOGO WATERMARKING SCHEME

Let L be the transform level, and h_i^b and x_j^b denote the wavelet coefficients of the host image and the logo, respectively, where b is the subband index and i, j are the coefficients indices.

2.1. Logo Embedding

The upper part of Fig. 1 is the block diagram of logo embedding, and the detailed procedure is described below.

Step 1. RWT and Scrambling: The host image and the logo are L- and $(L-1)$-level RWT decomposed, respectively.

Step 2. Embedding in Significant Positions: With 1-level less decomposition, the logo low-low frequency band (LL) is embedded into the host high-high subband (HH) of the highest level since a small distortion of the host LL can cause a relatively large visual artifact. For the rest subbands, the logo coefficients are embedded into the corresponding host subbands with the same decomposition level and orientation. The host image is analyzed to locate good embedding positions based on the HVS model [5], which includes frequency band, luminance and texture and has been proven effective in watermarking by [5][4]. The perceptual weights q_i^b are calculated and sorted in a descending order for a given subband b. Then the top P percentage most significant coefficients are selected and denoted as h_i^b. By using the logo subband statistical information, the quantization step-sizes Δ_b are optimally derived in Section 3. The embedded host coefficients are thus given by,

$$\hat{h}_i^b = h_i^b + \lfloor (q_i^b \cdot x_j^b)/\Delta_b \rfloor \tag{1}$$

where $\lfloor \cdot \rfloor$ is the truncation operation.

Step 3. IRWT: After the inverse RWT of the revised host coefficients, the watermarked image is generated.

2.2. Logo Extraction

The lower part of Fig. 1 shows how the logo is extracted. Since compensation for the potential attacks is not a focus of this work, we simply average multiple copies of the extracted logo to facilitate the theoretical derivation in Section 3.

Step 1. RWT: Perform L-level RWT on both the host image and the watermarked image.

Step 2. Recovery: The same perceptual weights in the embedding procedure are calculated based on the original host to find the embedding positions, while only the logo subband variance are needed to obtain the quantization step-sizes Δ_b. Thus the copies of logo coefficients are recovered by,

$$\tilde{x}_j^b = (\hat{h'}_i^b - h_i^b) \cdot \Delta_b / q_i^b \tag{2}$$

where $\hat{h'}_i^b$ is the possibly distorted watermarked image. A logo coefficient could be embedded for multiple times as long as the embedding percentage P is not too small. Our simple way is to average all the corresponding copies of the logo,

$$\hat{x}_j^b = \lfloor (\sum \tilde{x}_k^b)/N_j^b \rfloor \tag{3}$$

where N_j^b is the number of the embedding times for that logo coefficient and is counted during the procedure.

Step 3. De-Scramble and IRWT: The extracted logo coefficients $\hat{x}_j^b$ are de-scrambled, and the inverse RWT is applied to generate the logo.

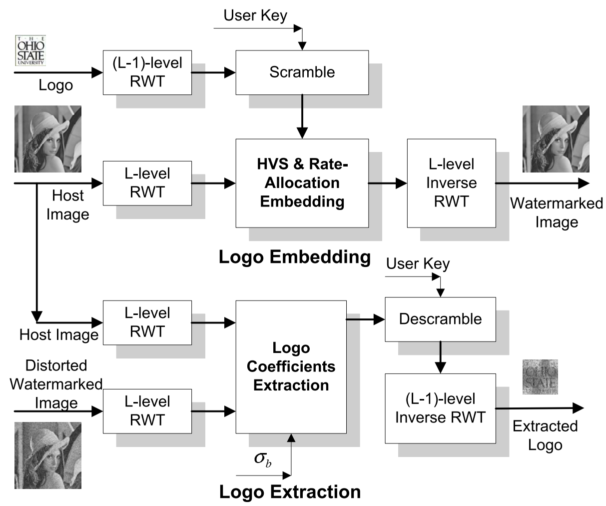

Fig. 1. The Block Diagram of Logo Watermarking Scheme

3. OPTIMAL RATE ALLOCATION

Logo is compressed and watermarked in the host. To maximize the fidelity of the extracted logo and to minimize the embedding distortion, we expose this tradeoff problem under a rate allocation framework. Similar to that in JPEG2000 [8], our problem becomes "given the overall embedding energy, what is the optimal rate allocation to minimize the distortion of the extracted logo?" In this paradigm, the objective is to find the optimal quantization step-sizes Δ_b for different logo subband coefficients, as mentioned in Section 2.

3.1. Problem Formulization

Assume in each logo subband b, coefficients follow a zero-mean Gaussian distribution with variance σ_b, which is a good approximation for general images [8]. Even for the LL subband, it is valid after the differential coding. Assume each logo coefficient has been embedded for K_b times on average for subband b. Let $d_H(\Delta_b)$ be the mean embedding distortion on the host, and $d_L(\Delta_b)$ denotes the mean distortion for each extracted logo coefficient. Given the embedding distortion Λ, the logo watermarking becomes a constrained optimization,

$$\text{Minimize}: \quad D_L(\Delta) = \sum_{b=0}^{B-1} \eta_b^L S_b^L d_L(\Delta_b)$$

$$Subject\,to: \quad D_H(\Delta) = P \sum_{b=0}^{B-1} \eta_b^H S_b^H d_H(\Delta_b) \leq \Lambda \tag{4}$$

where $B = (3L-2)$ is the number of logo subbands. η_b is the fraction of coefficients in subband b. S_b is the synthesis gain, and $S_b = 1$ if the wavelet filters are ortho-normal.

3.2. A Simplified Case

When the embedding percentage P is relatively small, then the top perceptual weights q_i^b could be assumed to be constant q^b for that subband. Let Δ_b be Δ_b/q^b, and then Eq. (1) is reduced to $\hat{h}_i^b = h_i^b + \lfloor x_j^b/\Delta_b \rfloor$. For a scalar quantization, $d_L(\Delta_b) = c\Delta_b^2$, where $c = 1/12$. The mean embedding distortion is the mean square of the integer part of quantized coefficients $d_H(\Delta_b) = E\{\lfloor x/\Delta_b \rfloor^2\}$. Easily we have $d_H(\Delta_b) = \sigma_b^2/\Delta_b^2 - \alpha$ for a constant α. We simply use the form $d_H(\Delta_b) = \sigma_b^2/\Delta_b^2$ instead since the quantity associated with α could be removed to the right of the constraint equation and be absorbed into Λ. Substituting $d_L(\Delta_b)$ and $d_H(\Delta_b)$ into Eq. (4) and adopting the Lagrange multiplier method, we obtain

$$L(\lambda) = \sum_{b=0}^{B-1} \eta_b^L S_b^L c\Delta_b^2 + \lambda \left(P \sum_{b=0}^{B-1} \eta_b^H S_b^H \sigma_b^2/\Delta_b^2 \right). \quad (5)$$

Taking the partial derivative against each Δ_b and combining the constraint, we have $\Delta_b = \sqrt[4]{\lambda\sigma_b^2 \frac{\eta_b^H S_b^H}{c\eta_b^L S_b^L}}$, where $\lambda = \left[\left(\sum_{i=0}^{B-1} \sigma_i \sqrt{c\eta_i^H \eta_i^L S_i^H S_i^L} \right) / \Lambda \right]^2$.

3.3. Subband Classification for Further Optimization

If P is relatively large, it is inappropriate to assume the top perceptual weights to be constant. One straight way to explore this spatial variety is to classify both these host weights and logo coefficients into multiple groups. A similar classification has been proven to gain about $1.43\,dB$ in compression problems in [8]. Assume that for subband b, logo coefficients are classified into N_c groups and embedded for K_b times. For simplicity, we limit N_c to be dyadic, such as $1, 4, 16$, etc. The P percent perceptual weights are thus classified into $K_b \cdot N_c$ groups. Hence in the embedding Eq. (1), the group average weight has to be written as $q_{k,n}^b$ and the step-sizes become $\Delta_{b,n}, k = 0, ., (K_b - 1); n = 0, ., (N_c - 1)$. Notice that classifying logo coefficients into groups is equivalent to having more subbands. The corresponding distortion to the host and that to the logo are given as,

$$D_H(\Delta) = \frac{P}{N_c} \sum_{b=0}^{B-1} \sum_{n=0}^{N_c-1} \eta_b^H S_b^H A_{b,n} \sigma_{b,n}^2 / \Delta_{b,n}^2 \quad (6)$$

$$D_L(\Delta) = \frac{1}{N_c} \sum_{b=0}^{B-1} \sum_{n=0}^{N_c-1} \eta_b^L S_b^L B_{b,n} c\Delta_{b,n}^2 \quad (7)$$

where $A_{b,n} = \frac{1}{K_b} \sum_k (q_{n,k}^b)^2$ and $B_{b,n} = \frac{1}{K_b} \sum_k 1/(q_{n,k}^b)^2$. By using the same technique as that in the simplified case, we obtain the optimal quantization step-sizes,

$$\Delta_{b,n} = \sqrt[4]{\lambda\sigma_{b,n}^2 (A_{b,n}\eta_b^H S_b^H)/(cB_{b,n}\eta_b^L S_b^L)} \quad (8)$$

Fig. 2. Watermarked Images

where $\lambda = \left[\frac{\sum_{i=0}^{B-1} \sum_{j=0}^{N_c-1} \sigma_{i,j} \sqrt{cA_{i,j} B_{i,j} \eta_i^H \eta_i^L S_i^H S_i^L}}{\Lambda N_c} \right]^2$.

4. NUMERICAL RESULTS

Experimental results verify the performance of the system, while comparison with an existing scheme demonstrates the improved robustness of our optimal rate allocation algorithm. We use an 8-bit 64×64 OSU logo and an 8-bit 512×512 Lenna as the host, all in gray-scale. Parameters are selected as $L = 4$, $P = 25\%$, $N_c = 4$, and the default transform of JPEG2000 standard, 5/3 filter, is chosen as the RWT, which enables the system to be integrated into JPEG2000 smoothly.

4.1. Imperceptibility Evaluations

The distortion constraints Λ, in both the simplified case and subband classification, are selected to generate the watermarked Lennas, with PSNR of $22.31dB$ (left) and $22.82dB$ (right) respectively, as shown in Fig. 2. Both are visually identical to the original host by subjective evaluations. The extracted logo of the latter is shown in Fig. 3 (a1), which is highly recognizable, but not the exact copy of the original one because of the lossy quantization by using RWT.

4.2. Robustness Verification & Peer Comparison

Various types of attacks, such as Gaussian noise, average & median filtering, and JPEG & JPEG2000 compression, are applied onto the watermarked Lenna, respectively, to test the robustness. Instead of displaying some clear extracted logos under mild distortions, we are pushing the attack parameters to the limit such that the extracted logos are just recognizable. In addition, the proposed scheme is compared with an existing one [4], which already achieved better robustness than [3].

In Fig. 3, the PSNR indicates the fidelity of the extracted logo, while the parameter in the parentheses is associated with that specific attack. To obtain a meaningful comparison, the scaling factor of the peer algorithm is tuned to achieve an embedding PSNR of $22.76\,dB$, which is almost identical to the proposed scheme, PSNR$=22.82\,dB$ and leads to a clear extracted logo, Fig. 3(b1). Then attacks are applied to both wa-

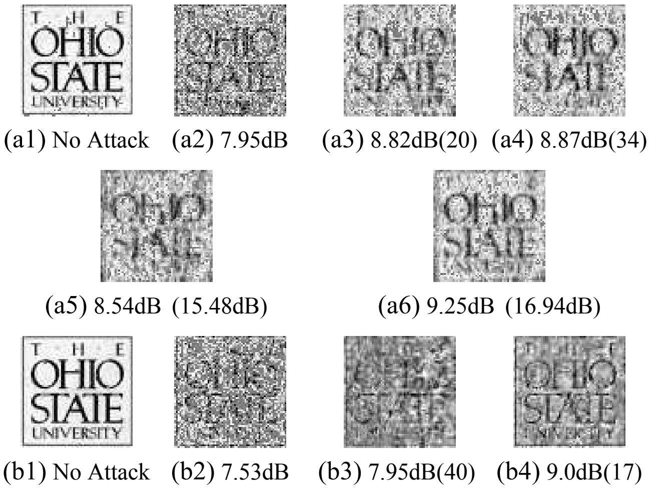

Fig. 3. Robustness Verification (a) & Peer Comparison (b)

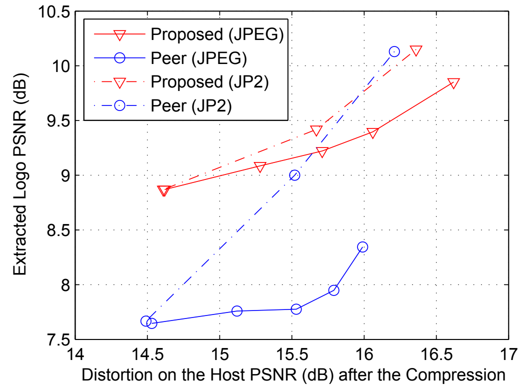

Fig. 4. Peer Comparison Under JPEG & JPEG2000

termarked hosts. First, watermarked Lennas in both methods are corrupted by additive Gaussian noise with a variance of 0.005. The PSNR for the host is reduced by $11.0\,dB$ for both methods, which means a rather severe distortion. The proposed method is slightly better in recognition than the peer one, as shown in Fig. 3(a2, b2). Then the extracted logos of the proposed scheme after 3×3 average and median filtering are shown in Fig. 3(a5, a6), respectively, in which $15.48dB, 16.94dB$ stands for the distortion level on the host. Those for the peer scheme are hardly recognizable and thus not shown here. Finally, the watermarked Lennas are compressed by JPEG with very low quality factors (QF), which means high compression ratios. The extracted logo of the proposed scheme with $QF = 20$, Fig. 3(a3), is even more recognizable than that of the peer scheme with $QF = 40$, Fig. 3(b3). Similarly, under JPEG2000 compression, Fig. 3(a4, b4) show that the result of the proposed scheme with compression ratio $CR = 34$ is comparable with the peer scheme with $CR = 17$. We also repeat both experiments under different compression ratios and plot the results in Fig. 4. Under JPEG compression (solid lines), the proposed scheme (triangle) achieves a higher fidelity in the extracted logo than the peer scheme (circle). In the JPEG2000 case (dashed lines), a similar conclusion is drawn for high compression ratios. In summary, the optimal rate allocation in embedding turns out to improve the robustness as well.

5. CONCLUSIONS

The main contribution of this work is to introduce the compression of the logo as a major optimization step in logo watermarking. By successfully exploiting the joint application of the HVS model and the rate allocation theory, a new multilevel decomposed algorithm is presented to achieve optimal energy allocation under the imperceptibility constraint. Numerical results verify that the our new method leads to improved robustness, and it is quite feasible for hardware implementation by using RWT.

6. REFERENCES

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