An Improved DWT Domain Statistical Image Watermarking System

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Abstract

In this paper, an efficient blind watermark detection scheme using DWT coefficients is proposed. The embedding scheme is multiplicative and done at second level of DWT decomposition by optimum choice of the embedding strength. The detection is based on the maximum likelihood ratio method. Neyman-Pearson criterion is used to minimize the missed detection probability subject to a fixed false alarm probability. The DWT coefficients are assumed to be modeled using the Laplacian distribution. In [10], the watermark is embedded in the vertical, horizontal and diagonal subbands in the III level. In this paper, we propose to embed the watermark only in the diagonal subband in level II, which results in better imperceptibility, robustness and capacity.

Keywords: Watermarking, DWT, Laplacian Distribution, Neyman-Pearson Criterion, Maximum Likelihood Detection, Decision Threshold.

1. Introduction

Nowadays, multimedia data is stored in the digital form which makes the processing and storage easy. But this leads to unauthorized duplication of the digital data. Digital watermarking is used to solve the above problem. It deals with techniques to embed the copyright information into a digital media by making small changes in the media content.

Watermarking can be done in either spatial domain or transform domain. Spatial domain approaches like LSB technique are not content based and are simple to implement. Transform domain approaches are more robust and can be implemented adaptively. Among the transform domain techniques DCT and DWT are commonly used.

The embedding of watermark in the cover image can be done either by additive or multiplicative rule. Usually, for additive embedding, correlation detection is used to detect the watermark. Additive methods are simple and used widely. Non-additive methods are very efficient because of their ability to achieve image dependent embedding.

The history and the basic principles of watermarking are discussed in [7], [9] and [13]. The attacks and benchmarks of performance are discussed in [14]. Cox et al in [6] compares watermarking with digital communication. A general watermarking framework and its demands are discussed in [4]. Typical watermark embedding issues and retrieval difficulties are described in [2] and [8] respectively.

For non-additive schemes in DWT domain, [10] and [12] suggest Maximum likelihood detection using Bayes Decision theory and Neyman-Pearson criterion for detection. [1] and [3] discuss statistical detections in DFT and DCT domain respectively. In paper [10] and [11],

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third level decomposition is employed and subbands in level 3, namely, horizontal (LH3), vertical (HL3) and diagonal (HH3) are embedded with watermarks. In this paper, we use the level 2 decomposition and embed only in diagonal subband (HH2). This improves the capacity, imperceptibility and robustness.

2. Methodology

a) Embedding Scheme [10]

Let $X = \{x_1, x_2, \dots x_N\}$ and $Y = \{y_1, y_2, \dots y_N\}$ be the vectors representing DWT coefficients of cover image and watermarked image in the HH2 region. A watermark $W = \{w_1, w_2, \dots w_N\}$ which is chosen from a set M, is embedded into X giving Y. W is inserted into the X by using multiplicative rule,

$$y_i = x_i(1 + \alpha w_i) \quad i = 1, 2, \dots N$$

where a is the embedding strength and x_i, w_i and y_i are the values of the random variable X_i, W_i and Y_i whose pdfs are $f_{X_i}(x_i)$, $f_{W_i}(w_i)$ and $f_{Y_i}(y_i)$ respectively for i = 1, 2, … N. The elements of the watermarks from the set M are independent and uniformly distributed in the interval [-1, 1].

b) Maximum Likelihood Detection [10]

If $W^* = \{w_1^*, w_2^*, \dots w_N^*\}$ is the embedded watermark, we can write $M = M_o \cup M_1$, where $M_o = \{W : W \neq W^*\}$ and $M_1 = \{W^*\}$. The null watermark $W = \{0, 0, \dots 0\}$, which indicates that no watermark is embedded, is already included in M_o.

Two hypothesis can be established as follows :

$$H_o = Y \text{ has } W^*$$
$$H_1 = Y \text{ does not have } W^*$$

The statistical decision test or watermark presence detection test is interpreted as deciding if the input of the detector is the outcome of the random process with the pdf conditioned to H1 and H0. It compares the ratio between the pdf conditioned to H0 and the pdf conditioned to H1 against a threshold as given below.

If the likelihood ratio,

$$l(y) = \frac{f_Y(y/M_1)}{f_Y(y/M_0)} > \lambda, \qquad (1)$$

then the watermark W* is detected

where $f_Y(y/M_j)$, j = 0, 1 are the conditional pdfs and λ is the decision threshold.

Since $\alpha < 1$, from [4]

$$f_Y(y/M_o) \approx f_Y(y/0) \qquad (2)$$

Assuming that the transform coefficients are statistically independent, (1) can be expressed as

$$l(y) = \frac{\prod_{i=1}^{N} f_{Y_i}(y_i / w_i^*)}{\prod_{i=1}^{N} f_{Y_i}(y_i / 0)} \qquad (3)$$

$$= \frac{\prod_{i-1}^{N} \frac{1}{1+\alpha w_i^*} f_{x_i}\left(\frac{y_i}{1+\alpha w_i^*}\right)}{\prod_{i-1}^{N} f_{x_i}(y_i)} \qquad (4)$$

Since log x is an increasing function of x, log l(y) will reach its maximum value when l(y) reaches its maximum. Hence, taking natural log on both sides

$$z(y) = \sum_{i=1}^{N}\left[\ln fx_i\left(\frac{y_i}{1+\alpha w_i^*}\right) - \ln f_{x_i}(y_i)\right] > \lambda \qquad (5)$$

$$\text{where } \lambda' = \ln\lambda + \sum_{i=1}^{N} \ln(1+\alpha w_i^*) \qquad (6)$$

is the modified decision threshold.

c) Decision Threshold [10]

The Neyman-Pearson criterion is used to find λ' to minimize the missed detection probability for a fixed false alarm probability, P_{FA}

Let, $P_{FA} = 10^{-9}$.

$$P_{FA} = P(z(Y) > \lambda'/M_o) = P(z(X) > \lambda') = \int_{\lambda'}^{\infty} f_{z(x)}\,(z(X))\; d\, z(x) \quad (7)$$

As the number of Z(x) is more than 30, central limit theorem can be applied and PDF of Z(x) can be assumed to be Gaussian.

Thus,

$$P_{FA} = \int_{\lambda'}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2_{z(x)}}} e^{\left(-\frac{[z(x)-\mu_{z(x)}]}{2\sigma^2_{z(x)}}\right)} dz(x) \quad (8)$$

which gives

$$\lambda' = \mathrm{erfc}^{-1}(2P_{FA})\ \sqrt{2\sigma^2_{z(x)}} + \mu_{Z(x)} \quad (9)$$

d) Laplacian Model [10]

Each of the DWT coefficients is modeled by the Laplacian PDF given below

$$f_{X_i}(x_i) = 0.5\, b_i \exp(-b_i\, |x_i - \mu_i|) \qquad -\infty < x_i < \infty \quad (10)$$

with $b_i = \sqrt{2}/\sigma_i$ where σ_i^2 is the variance of X_i and μ_i is the mean of X_i. Substituting (10) in (4),

$$z(y) = \sum_{i=1}^{N} b_i \left[\, |y_i - \mu_i| - |1+\alpha w_i^*|^{-1} |y_i - \mu_i - \mu_i \alpha w_i^*| \,\right] > \lambda' \quad (11)$$

Mean and variance are derived to be

$$\mu_{Z(x)} = \sum_{i=1}^{N} [1 - |1+\alpha w_i^*|^{-1} \{b_i\, |\mu_i \alpha w_i^*| + \exp(-b_i\, |\mu_i \alpha w_i^*|)\}] \quad (12)$$

and

$$\sigma^2_{z(x)} = \sum_{i=1}^{N} [1 + |1+\alpha w_i^*|^{-2} \{2 - \exp(-2b_i\, |\mu_i \alpha w_i^*|)]$$

$$-2|1+\alpha\, w_i^*|^{-1} \exp(-b_i |\mu_i \alpha\, w_i^*|)$$

$$-2b_i\, |\mu_i \alpha\, w_i^*| \exp(-b_i |\mu_i \alpha\, w_i^*|)\ \{|1+\alpha\, w_i^*|^{-1}$$

$$+ |1 + \alpha\, w_i^*|^{-2}\}] \quad (13)$$

Substituting (12) and (13) in (9) the decision threshold λ' is obtained.

3. Experimental Results And Discussions

Images of Lena, Cameraman and Crowd at the size of 512 x 512 are used as cover images and are shown in Fig. 1. Lena contains little detail; Cameraman contains an intermediate amount of detail and crowd contains a large amount of detail [5].

Lena **Cameraman** **Crowd**

Figure 1: Cover Images

Each cover image is transformed by DWT. A Daubechies filter is used to obtain a second and a third level decomposition.

3.1 Results of level III Embedding

In [10], embedding is done in the high frequency subbands LH3, HL3 and HH3. Total number of coefficients after combining the three bands is N = 12,288. Thus, watermark can have a maximum of 12,288 elements only. Each element has been assumed to be either 1 or −1. If a coefficient belongs to the particular band, mean μ_i and variance σ_i^2 are estimated from the equations,

$$\mu_i = \frac{1}{N_B} \sum_{i=1}^{N} y_i \quad (14)$$

$$\sigma_i^2 = \frac{1}{(N_B - 1)} \sum_{i=1}^{N} (y_i - \mu_i)^2 \quad (15)$$

where number of coefficients in one band, $N_B = 4096$ and y_i is the value of DWT coefficient in band B of the watermarked image. The results of detection are listed in Table 1 & 2. Let $\alpha = 0.3$.

Gaussian noise has zero mean and variance 0.5. Blurring is caused by circular filter of the size 31 x 11. Rotation is up to 10° in the counter clockwise directions. JPEG compression is done to offer 50% quality. Cropping is done to obtain an image whose size is 300 x 300. Mean filter filters the image by using adaptive wiener filter, using neighbourhoods of size 4 x 4.

Table 1 : Results of level III Embedding (without attacks)

Cover image	PSNR for α= 0.3 (Peak Signal to Noise Ratio)	Number of successful detections for 10 trials (without attacks)
Lena	37.24	10
Cameraman	34.93	10
Crowd	30.89	10

Table 2 : Results of level III Embedding (with attacks)

Image	Number of successful detections for 10 trials (with attacks)					
	Gaussian noise	Mean filter	Blur	Rotation	JPEG Compression	Crop
Lena	10	10	5	0	10	10
Cameraman	10	10	4	0	10	10
Crowd	10	10	9	0	10	10

The embedded watermark is chosen from a set of 100 randomly generated watermarks of length N. Number of trials is 10. If a value increases beyond 0.3, the robustness will improve and number of successful detections will be more. But, the PSNR value which is already less will decrease still.

3.2 Results of Proposed Level II Embedding

In our proposed method, embedding is done only at HH2 subband because its variance is the lowest.

1. Capacity

HH2 subband's size is bigger than that of HL3, LH3 & HH3 put together. Hence, the capacity of the proposed method is 16,384, whereas, the capacity of III level embedding in HL3, LH3 & HH3 is only 12,288. Thus, capacity of the proposed method is better.

2. Imperceptibility

PSNR is a measure of imperceptibility. If the embedding strength a increases, imperceptibility will reduce and robustness will improve. Similarly, if a decreases, imperceptibility will improve and robustness will reduce. Thus, there is always a trade off between imperceptibility and robustness.

In Table 3, PSNR values are compared. It is evident that the proposed level II embedding exhibits better imperceptibility because only high frequency information is subjected to distortion in our case.

Table 3: Comparison of PSNR Values of Existing and Proposed Methods

Cover image	α	PSNR value of existing level III embedding	PSNR value of proposed level II embedding
Lena	0.5	32.00	44.97
Cameraman	0.5	30.49	43.64
Crowd	0.5	26.49	40.63

3. Robustness

Number of successful detections, when the watermark image is under attack, indicate the amount of robustness.

A watermark chosen from a set of 100 watermarks is embedded and detected. Table 4 and 5 show the number of successful detections for 10 trials without and with attacks. The numbers in Table 5 indicate higher robustness.

As the imperceptibility of the proposed II level embedding is high, we have chosen to embed with a = 0.5 which yields better robustness.

Table 4 : Results of Level II Embedding (Without Attacks)

Cover image	PSNR for α=0.3	Number of successful detections for 10 trials (without attacks)
Lena	44.97	10
Cameraman	43.64	10
Crowd	40.63	10

Table 5 : Results of Level II Embedding (With Attacks)

Cover image	Number of successful detections for 10 trials (with attacks)					
	Gaussian noise	Mean filter	Blur	Rotation	JPEG Compression	Crop
Lena	9	10	10	10	10	10
Cameraman	9	10	10	10	10	10
Crowd	10	10	10	10	10	10

Comparing Tables 1 & 2, with Tables 4 & 5, we can conclude that level II embedding yields better robustness.

4. Conclusion

A maximum likelihood detection scheme based on Laplacian modeling of coefficients of DWT transformation is implemented. The results obtained at level II, HH2 subband embedding are better than the results obtained using the existing method of embedding at level III.

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