Chapter 7

Multi-resolution Watermarks

A digital watermark is an identifying digital pattern that is inserted into a digital document and can be visible or invisible. For audio or video data, the watermark is a signal that is added such that it cannot be removed without damaging the original data. Such watermark signals are usually imperceptible. In this chapter we only consider digital watermarking of digital images. Images can be watermarked in spacial domain or transform domain.

Our approach is mainly algorithmic in that we embed a binary watermark image, e.g. a Logo, in wavelet transform domain. In the section 7.1 we discuss advantages of using simple images, (small binary images), as the watermark signals. In the section 7.2 we discuss issues relating to resolving rightful ownerships. The sections 7.3, 7.4, and 7.5 describe our watermarking algorithm. Firstly in section 7.3, I discuss the feature based watermarking process in that each watermark image (a binary image) bit is embedded to a feature of the image in the wavelet transform domain. In section 7.4, I will discuss Multi-resolution watermark Channels in that we discuss a structure and an order in which the watermark image bits are embedded. In section 7.5, I will discuss a wavelet transform which can be used for binary images.

7.1 Copyright Enforcement with Watermark Images

All watermarking techniques cannot be used for all the scenarios which demand some kind of image security. The watermarking techniques should be developed to provide valid legal arguments to particular image security applications. In [54] its argued that watermarking algorithms which uses the original image in the detection process cannot be successfully used for resolving rightful ownership. Our watermarking algorithm require the original image in the detection process and is designed for copyright enforcement applications where the authenticity of the original image does not arise.

Copyright enforcement deals with the illegal distribution of copies. Along this distribution chain, images may undergo legitimate or illegitimate modification such as compression. Such modification processes may introduce noise into the detected watermark signal. Such noise may completely change the meaning of the watermark bit sequence if it represents a message. If the watermark signal is an image, we may still recover the meaning of the watermark after noise removal of the detected watermark image.

7.2 Resolving Rightful Ownerships

Consider one generates a watermarked image I_w which is visually close to the original image I using a watermark W. In [42], they argue that counterfeit watermarking schemes can allow multiple claims of ownerships. We call this *scenario 1.* In [54], they present a simpler scenario in which rightful ownership can not be resolved, which we call *scenario 2*. In both these scenarios they argue that the true owner should be able to detect the watermarks without using a second image (original image). In the following, we will discuss a modified *scenario 1* which allow watermark detection with the original image.

In *scenario 1*, consider the situation where the possessor of I_w creates a counterfeit original I_c by subtracting his own watermark W_c from I_w such that I_w is a watermarked version of the fake original I_c by the watermark W_c. In this situation the suspected image I_w is a watermarked version of images I and I_c by watermarks W and W_c respectively, and hence rightful ownership cannot be resolved.

We argue that the problem of *scenario 1* is the resolution process. Assume the watermark detection is done by the court of law or any trusted party who, upon the access to the watermarks and the original images, do not give them to the other party. Suppose the ownership is claimed by a particular party by detecting a watermark in the suspected watermarked image as well as suspected original image. If the watermark is not destroyed by the counterfeit original image creation process, the true owner can detect the watermark W in both I_w and I_c. But the fake owner can detect the watermark W_c in I_w but not in I since W_c is not embedded in I. Thus the fake owner can only claim the ownership by removing W from I_w. The robustness of the embedding process must guarantee that such removal is hard if not impossible.

Scenario 2 is more powerful and simpler than *scenario 1*. In this case, the possessor of I_w simply argue that I_w is the original image and the owner of I somehow took I_w and subtracted W to create I. As a solution to *Scenario 2* and *scenario 1*, Craver et. all. [42] suggest that the watermarking schemes should not be invertible.

7.3 Feature Based Watermarking

When each watermark bit is embedded into a feature extracted from the image, we call its feature based embedding [4, 55, 6]. We consider features which are blocks of values of the image in wavelet domain. When the watermark is an image, the size of such feature blocks tends to be small due to the large number of watermark bits which are required to be embedded.

Watermarking will not be successful if the attacker can easily see or recover the stored contents of the feature blocks. By transforming the watermark bit into a broadband noise signal, we can make the attackers task harder. We associate a broad band noise signal to each watermark bit. These broad band signals (watermark noise signals) can possibly be the same or different for different watermark bits which comprise the watermark image.

Watermark Image Embedding

We add the broad band noise signal to the feature block to embed the watermark bit 1. We make no changes to the feature block to embed the watermark bit 0. Let the feature block coefficients are represented as α_i and the broad band noise signal as β_i, then after embedding the watermark bit 1 we change the feature block coefficients α_i to $\alpha_i^w = \alpha_i + \beta_i$.

Watermark Image Detection

We detect the watermark bit w_k^s by correlating the feature block coefficients, α_i^s , of the suspected image with the associated broad band noise signal β_i. Let $c_k = \sum \alpha_i \beta_i$, then for an appropriate threshold t_k,

$$w_k^s = \begin{cases} 1 & \text{if } \sum \alpha_i^s \beta_i - c_k > t_k \\ 0 & \text{if } \sum \alpha_i^s \beta_i - c_k \leq t_k \end{cases}$$

For most watermarking techniques where feature block size is very large, it is natural that α_i and β_i are uncorrelated such that $\mathcal{E}(c_k) = 0$. But since our feature block size is small we will not make such an assumption.

Threshold Selection

Watermark detection is successful only if the threshold t, which we assume temporarily independent of feature block, is chosen such that the expected correlation of β_i and the noise γ_i introduced by image modification, is within $-\left(\sum \beta_i\beta_i - t\right)$ and t, i.e $\sum \gamma_i\beta_i < t < \sum \beta_i\beta_i + \sum \gamma_i\beta_i$. The left hand bound is for correct detection of $w_k = 0$ while the right hand bound is for the correct detection of $w_k = 1$. Such a threshold exists with no errors only if

$$\text{Sup}_k \sum \gamma_i\beta_i < \text{Inf}_k \sum \beta_i\beta_i + \sum \gamma_i\beta_i.$$

Unfortunately, this relation is not satisfied in practical situations. For watermark images stored in watermark storage channels which are discussed in the following section, we have experimentally found an optimum threshold. Let e_1 be the number of errors for a watermark image where all the pixels are 1, at a particular compression ratio. Also let e_0 be the number of errors for a watermark image where all the pixels are 0, at the same compression ratio. The graphs of e_1 and e_0 are given in Figure 7.1. The optimum threshold, t_{op}, exits when $e_1 + e_0$ is minimum. Also at this point e_1 is approximately equal to e_0. We also observed that t_{op} is approximately equal to $\frac{1}{2}\sum \beta_i\beta_i$ as expected. We also observed that this threshold is approximately the same at

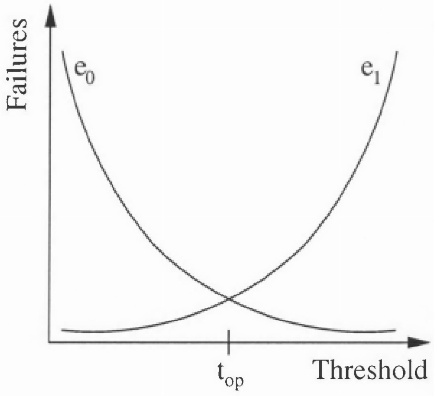


Figure 7.1: Threshold failure statistics

all the compression ratios as long as we perform the calculations up to the breaking point of the channel. When the broad band watermark noise signal is different from one feature block to another we use $\frac{1}{2}\sum \beta_i \beta_i$ as the feature block dependent threshold.

7.4 Multi-resolution Watermark Channel

We construct a watermark storage channel which has multi-resolution characteristics, with which we are able to extract binary watermark images at different resolutions. In our framework a particular compression ratio represents a particular watermark channel resolution. We will first define *binary watermark storage location* as follows.

Definition 11 *A binary watermark storage location x is a binary variable derived from the image I such that $E(x = 0) < k$ and $E(x = 1) < k$ for given error bound k. The function $E(x)$ is the error caused by setting the binary variable x true or false.*

A particular channel resolution V_{r_i} consists of a set of such storage locations where r_i is a compression ratio. The channel at different resolutions are related as

$$V_{r_0} \subseteq V_{r_1} \subseteq V_{r_2} \subseteq \cdots$$

where

$$r_0 \leq r_1 \leq r_2 \leq \cdots$$

We allocate binary watermark storage locations according to the following criteria. Let $STABLE(I, r_k)$ represent the set of watermark storage locations such that $x(I) = x(I_{r_k})$ for both $x(I) = 1$ and $x(I) = 0$ where $x(I)$ represents the value of storage location x of original image I and $x(I_{r_k})$ represents the value of storage location x of original image compressed at compression ratio r_k.

Definition 12 *A binary watermark storage location x is said to be in V_{r_k} of I if $x \in STABLE(I, r_k)$ for all i such that $r_k \leq r_i$.*

For a given image, error bound and a compression algorithm, we will sort the storage locations to get $V_{r_0}, V_{r_1} - V_{r_0}, V_{r_2} - V_{r_1}, \cdots$. The multi-resolution values of the binary watermark image is stored in the channel in the order above.

We construct the watermark storage channel assuming that all the watermark storage locations are independent from each other, i.e whether a particular storage location belongs to a particular resolution is not determined by the values of other storage locations. With this assumption and using a broad band watermark noise signal for all the feature blocks, we use the following algorithm to construct the multi-resolution watermark channel.

Algorithm 2

1. *Embed True at watermark storage locations resulting from the wavelet transform. Apply the inverse wavelet transform and denote the resulting image as* I^{true}*. Similarly, embed false and denote the resulting image as* I^{false}*. Let* V_{r_k} *be the storage locations at resolution* $r_k = 1$*. Chose a set of compression ratios* $\{r_i\}$ *such that* $\cdots \leq r_{k-1} \leq r_k$*. Let* $i = k$*.*

2. *Let*
$$\begin{aligned} V_{r_{i-1}} = \ & STABLE(I^{true}, r_{i-1}) \cap \\ & STABLE(I^{false}, r_{i-1}) \cap \\ & V_{r_i} \end{aligned}$$

3. *Repeat step 2 for* $i = k, k-1, k-2, \cdots$*.*

Figures 7.5, 7.6, and 7.7 shows the performance of such independent watermark storage channels.

7.5 Multi-scale Transform of the Binary watermark Image

We transform the watermark image to a multi-resolution representation using the filter bank as shown in Figure 7.2. Successive application of the filter bank to low pass sub-band yields the multi-resolution representation. We used separable filters. Other such binary wavelet filters [7] can also be used. After our work we have learned that our binary filter bank is a special case of morphological wavelet filters [15].

The filter bank follows the lifting approach [51]. In the analysis side, original signal is separated into even and odd components by the down-sampling operators. The odd values are predicted from the even values and

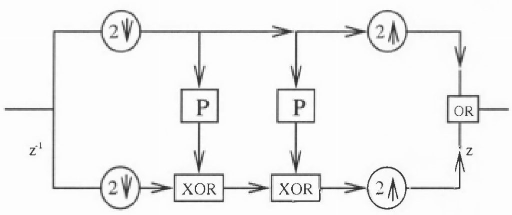


Figure 7.2: 2-channel Binary Signal Filter Bank

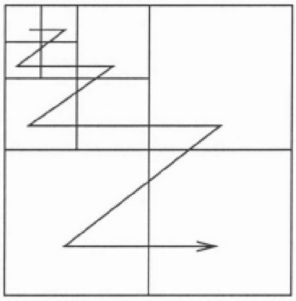


Figure 7.3: Scan order of coefficients

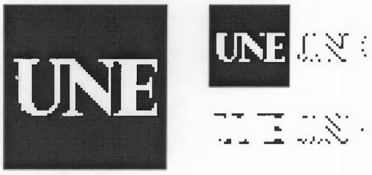
the prediction error is calculated using the XOR operator. Notice, the perfect reconstruction of the filter bank is guaranteed since

$$(o\ XOR\ e)\ XOR\ e) = (o\ XOR\ (e\ XOR\ e))$$

$$= o\ XOR\ false = o$$

where o is an odd value and e is a predicted odd value. Multi-resolution representation of our watermark image is shown in 7.4 (b).

This multi-resolution representation of the watermark image is scanned in the order shown in figure 7.3 and stored in the multi-resolution watermark channel.



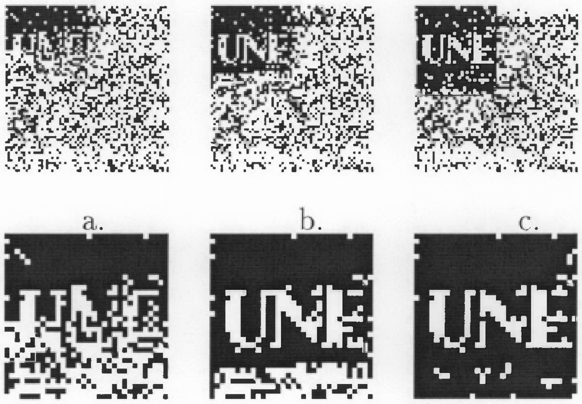
a. b.

Figure 7.4: (a) The original UNE watermark image (b) One level multi-resolution transform of the watermark image.

7.6 Results and Discussion

We have used the Lena image and the bike image used in JPEG2000 standardization process for watermarking purposes. The watermarked Lena image is given in Figure 7.8 for the feature block size of 2x2. We have measured the compression performance of the watermarking algorithm under SPIHT compression. The subjective detection performance after partial reconstruction at 20:1, 16:1 and 13.3:1 compression ratios for Lena and for the bike image are given in Figure 7.5 and 7.7 respectively. Figure 7.6 shows the full reconstruction of the detected watermark image at compression ratios 10:1, 8.89:1 and 8:1 for Lena image. We applied simple noise removal algorithm which removes isolated bits and connected bits of size 2. All the detected watermark images show that the channel has a clear breakdown size which decreases with increasing compression ratios.

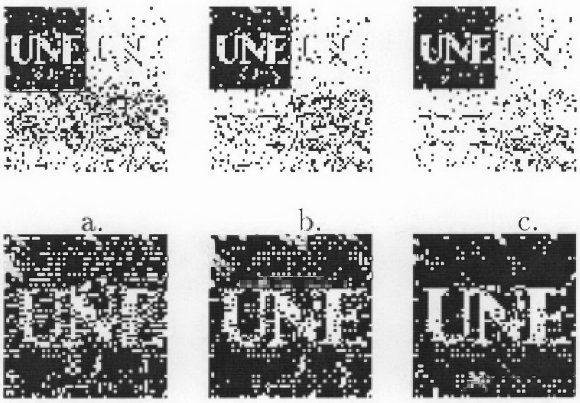
Our future work will be to improve the embedding algorithm to include perceptual criteria, find better multi-resolution watermark channel construction algorithms and to embed multiple watermark images.



a. b. c.

d. e. f.

Figure 7.5: The detected watermark image for Lena at (a) 0.4bpp (b) 0.5bpp (c) 0.6bpp and the partial reconstruction from the low pass image after noise removal at (d) 0.4bpp (e) 0.5bpp (f) 0.6bpp.



a. b. c.

d. e. f.

Figure 7.6: The detected watermark image for Lena at (a) 0.8bpp (b) 0.9bpp (c) 1bpp and the full reconstruction after noise removal at (d) 0.8bpp (e) 0.9bpp (f) 1bpp.

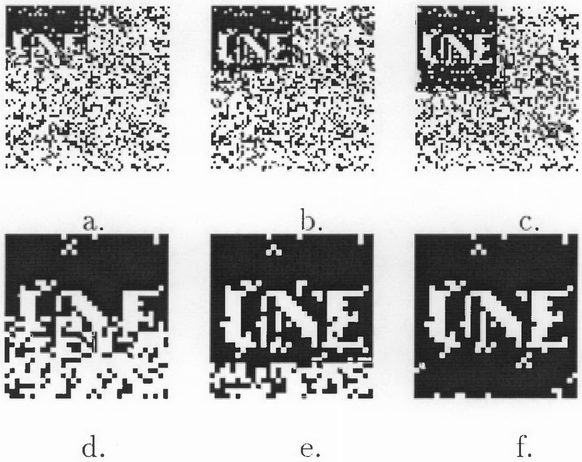


Figure 7.7: The detected watermark image for bike at (a) 0.4bpp (b) 0.5bpp (c) 0.6bpp and the partial reconstruction from the low pass image after noise removal at (d) 0.4bpp (e) 0.5bpp (f) 0.6bpp.

Figure 7.8: The watermarked Lena image

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