A New Adaptive Image Watermarking Algorithm Based-on DWT

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Abstract

A new adaptive image watermarking algorithm is proposed in this paper. A perceptual model based on the computation of NVF (noise visibility function) is exploited in the proposed watermarking scheme. The original image is first transformed in the wavelet domain and the embedding factor is decided through computing the NVF of the mid-frequency; then the watermark is embedded in the selected subband with different embedding factors; finally, the watermarked image is obtained by reverse wavelet transform. Experimental results show that the proposed method is adapted to various gray images with different characteristics and robust to wide verity of image processing operations.

Keywords: Image Watermarking; Discrete Wavelet Transform; Adaptive; Robustness; NVF

1. Introduction

With the rapid development of Internet and multimedia technology, digital products (such as image, audio and video) can be easily accessed and transmitted. Therefore, the copyright protection of these multimedia products has become an important issue and so much attention has been drawn toward the development of effective digital products protection. Digital watermarking as an effective tool for copyright protection has been received considerable attention during the last few years.

Digital watermarking is defined as a technique of embedding additional information into digital product while preserving perceptual quality of watermarked data. The information called watermark can be detected or extracted for purpose of owner identification or integrity verification of tested data [1, 2]. Complement to conventional encryption, watermarking allows further protection of the data after decryption. As we know, encryption procedure aims at protecting the data during its transmission. Once decrypted, the data is not protected anymore. However, by adding watermark, we add a certain degree of protection to the data even after the decryption process has taken place. There are two fundamental requirements for digital watermarking [3]: transparency and robustness. Transparency means that the introduction of watermark should not degrade the quality of original data. In other words, the embedded watermark should not be perceived by human visual/audio system. Robustness refers to that the watermark can still be detected or extracted after the watermarked data has undergone common signal processing operations such as lossy compression, noise addition, low pass filtering, sharpening, etc.

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Recent watermarking algorithms can be broadly classified into two categories [4]: spatial domain algorithms and transform domain algorithms. Spatial domain algorithms directly alter the original data, which are less complex yet fragile to common attacks. In transform domain algorithms, the values of some transform coefficients are modified to embed the watermark. Transform domain methods are more robust compared to spatial domain methods and have become the focus of recent researches. Among the transform domain algorithms, DWT (discrete wavelet transform) based watermarking algorithms are gaining more popularity due to its good space-frequency localization, its compatibility with the JPEG2000 compression standard.

In this paper, we will propose a new adaptive image watermarking algorithm. The paper is organized as follows: Section 2 briefly discusses the discrete wavelet transform of digital images. Section 3 gives the perceptual model which is based on NVF. The proposed watermarking algorithm is described in section 4. Section 5 presents the experimental results and section 6 concludes the paper.

2. Discrete Wavelet Transform of Digital Images

The discrete wavelet transform is widely used in signal processing applications such as signal analysis, denoising, compression, etc. The DWT decomposes a signal into a lowpass and a highpass signal by using a pair of QMF filters. The lowpass signal is called an approximation and the highpass signal is called a detail [5]. This process of signal decomposition can be repeated by applying a second QMF filter pair on the just obtained approximation. Two-dimensional signals such as images are decomposed by DWT into subbands that vary in spatial frequency and orientation.

Due to its great characteristics, DWT has been widely used in digital watermarking. Advantages of embedding the watermark in the wavelet domain are as follows [6]: DWT provides good space-frequency localization for analyzing image features such as edges or textured areas.

Watermarking in the wavelet domain is compatible with the JPEG2000 compression standard [7]. The dyadic frequency decomposition of the wavelet transform resembles the signal processing of the HVS and thus permits to excite the different perceptual bands individually.

Discrete wavelet transform has linear computational complexity of $O(\log n)$ whereas the DCT is $O(n \log n)$. The difference is important only when the DCT is applied to the whole image, but when compared to a block based DCT wavelet transform is more expensive.

The wavelet transform is flexible and can adapt to a given set of images or a particular type of application.

Fig. 1 shows the 1 level wavelet decomposition of Lena image. The upper left block represents a smooth approximation of the original image. The other subbands contain details at horizontal, vertical, and diagonal directions respectively.

Among all subbands, high frequency subbands represent the detail and edge components in an image which are less sensitive to human eye, but they are more easily attacked by common operations. Conversely, the low frequency subband is more robust but little alteration can be perceived by HVS (human visual system). To get a trade-off between transparency and robustness, we select the mid-frequency subband to
embed the watermark.

![Fig.1 Level DWT of Image Lena](image)

3. Perceptual Model Based-on NVF

Nowadays, digital image watermarking is widely applied as an effective technique for authentication and copyright protection for images. Based on global information about the image characteristics, most schemes embed the watermarking information in the whole cover image with the same strength regardless of the local properties of the image. This embedding strategy may lead to visible artifacts especially in the regions which are characterized by small variability. In order to decrease these distortions the given watermark strength has to be decreased. This, however, reduces drastically the robustness of the watermark against different kinds of attacks, since the image regions which generate the most visible artifacts determine the maximum strength of the watermark information to be embedded.

We provide this problem an effective solution which embeds the watermark into the cover image according to the local properties of the cover image, i.e. the watermarking algorithm will be content adaptive [8].

Many researchers develop content adaptive schemes on the basis of the characteristics of the human visual system (HVS) [9-11]. In [9], the masking of the HVS that can be used to predict individual and global masking thresholds of multimedia data was emphasized and exploited to design transparent watermarking schemes. In [10], the perceptual knowledge was incorporated into the watermarking scheme. Based on a suitable measure of contrast and a masking model, a weighting method for the spread spectrum image watermarking was proposed in [11] to minimize the visual distortion and increase the robustness of the watermark. Another group of adaptive methods is based on the image compression background and practically exploits three basic conclusions: (1) all regions of high activity are highly insensitive to distortion; (2) the edges are more sensitive to distortion than highly textured areas; (3) darker and brighter regions of the image are less sensitive to noise. The typical examples of this scheme are given in [12, 13].

All the content adaptive approaches discussed above neither lead to visible artifacts nor have high computational complexity. In this paper, we will exploit a perceptual model based on NVF which was proposed in [14]. The model uses NVF (noise visibility function) to describe noise visibility in an image. The most known form of NVF is given as [15-17]:

$$ NVF = \frac{1}{1 + \theta \sigma_i^2(i, j)} $$  \hfill (1)
Where $\sigma^2_x(i, j)$ denotes the local variance of the image in a window centered on the pixel with coordinates $(i, j)$ and $\theta$ is a tuning parameter corresponding to the particular image. Local variance is given by:

$$\sigma^2_x(i, j) = \frac{1}{(2L+1)^2} \sum_{k=-L}^{L} \sum_{l=-L}^{L} (x(i+k, j+l) - \bar{x}(i, j))^2$$  \hspace{1cm} (2)

With $$\bar{x}(i, j) = \frac{1}{(2L+1)^2} \sum_{k=-L}^{L} \sum_{l=-L}^{L} x(i+k, j+l)$$  \hspace{1cm} (3)

Where a window sized $(2L+1) \times (2L+1)$ is considered. The image-dependent tuning parameter is given in the following form

$$\theta = \frac{D}{\sigma^2_{x_{\text{max}}}(i, j)}$$  \hspace{1cm} (4)

Where $\sigma^2_{x_{\text{max}}}(i, j)$ is the maximum local variance for a given image and $D \in [50,100]$ is an experimentally determined parameter[8]. An example of NVF for image Lena is shown in Fig.2. The values of NVF range from zero to one. Higher values of NVF (brighter regions in the image on Fig.2b) indicate flat region and vice versa smaller values of NVF (darker regions in the image on Fig.2b) indicate textured regions or regions with edges.

Based on the above perceptual model, we derive the embedding factor as:

$$\Lambda = (1 - NVF) \cdot S_F + NVF \cdot S_{ET}$$  \hspace{1cm} (5)

Where $S_F$ and $S_{ET}$ denote the watermark strength in textured and flat image regions respectively. Therefore, watermark embedding in an image by using NVF can be expressed in the following form:

$$X^*(i, j) = X(i, j) + \Lambda(i, j) \cdot w(i, j)$$  \hspace{1cm} (6)
Where $X(i, j)$ and $X^*(i, j)$ are pixel values of the original and watermarked image respectively, and $w(i, j)$ are watermark sequence. According to this equation the embedded watermark is image content adaptive because the energy of the watermark is higher in textured and edges region than in the flat regions of the image.

4. Proposed Watermark Algorithm

A watermarking algorithm usually includes two parts: watermark embedding and watermark detection. In this section, we will present the proposed algorithm.

4.1. Watermark Embedding

The process of embedding the watermark into the original image can be formulated as follows:

1. Watermark Generation. According to Cox [18], Watermark composed of independent, identically distributed (i.i.d.) samples drawn from a Gaussian distribution gives resilient performance against common attacks and it also provides low false positive and false negative detection. So we choose Gaussian random sequence as watermark.

2. Discrete Wavelet Transform of the Original Image. The original image is wavelet decomposed into 3 levels and we select the $HL_3$ subband to embed the watermark.

3. Embedding Factor Computation. Based on the perceptual model, we compute the values of NVF for $HL_3$ and else the embedding factor $\Lambda_{HL_3}$.

4. Watermark Embedding. According to the equation (6), the watermark is embedded into the $HL_3$ as follows:

$$HL_3^*(i, j) = HL_3(i, j) + \Lambda_{HL_3}(i, j) \cdot w(i, j)$$

(7)

5. The watermarked image is achieved through computing IDWT of modified and unmodified DWT coefficients.

6. The objective evaluation of watermarked image quality is performed by the PSNR, which is defined as:

$$PSNR = 10 \log_{10} \frac{255^2}{\frac{1}{N \times N} \sum_{j=1}^{N} \sum_{i=1}^{N} [I(i, j) - I^*(i, j)]^2}$$

(8)

Where $I^*$ and $I$ are respectively the watermarked and original image and $N \times N$ is the size of the image.
4.2. Watermark Detection

To examine the existence of the embedded watermark, both the original and the watermarked images (probably attacked) are needed. The detection progress is described as follows:

1. The original and the watermarked images (probably attacked) are both 3 level decomposed. The embedding factor is computed by the equation (5).

2. According to the embedding equation (7), each watermark bit is extracted. Then all watermark bits are combined to form the extracted watermark sequence $w^*$.

3. We measure the similarity of $w$ and $w^*$ by

$$sim(w, w^*) = \frac{w^* \cdot w}{\sqrt{w^* \cdot w^*}}$$

(9)

5. Experimental Results

The performance of the proposed algorithm is tested on various types of images. All tested images are grayscale 8-bit of size $256 \times 256$. The Haar wavelet is used. The watermark is 1000 i.i.d. (independent identically distributed) Gaussian random sequence and the secret seed is 200th. We experimentally set $S_F = 12.707$ and $S_{ET} = 0.5$ which yield better results.

Fig.3 shows the original image Lena and its watermarked copy. The PSNR value of the watermarked Lena is 47.1719. It is obvious that the watermarked copy is undistinguishable from the original image.

![Fig.3 The Original Image Lena and its Watermarked Copy](image)

Fig.4 illustrates the response of the watermark detector to 1000 randomly generated watermarks, with the original watermark placed in the 200th. The positive response to the correct watermark is very much stronger than the response to incorrect watermarks, suggesting that the algorithm has very low false positive detection rates.
The PSNR values and detector responses for different kinds of images are shown in Table 1. We can derive from the table that the proposed algorithm is adapted to images with various characteristics.

Table 1 The Values of PSNR & DR for Different Kinds of Images

<table>
<thead>
<tr>
<th>Images</th>
<th>PSNR</th>
<th>DR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lena</td>
<td>47.1719</td>
<td>27.4448</td>
</tr>
<tr>
<td>Mandril</td>
<td>46.5134</td>
<td>29.8012</td>
</tr>
<tr>
<td>Peppers</td>
<td>47.2875</td>
<td>27.8620</td>
</tr>
<tr>
<td>Boat</td>
<td>48.3608</td>
<td>25.8760</td>
</tr>
<tr>
<td>Aerial</td>
<td>46.0542</td>
<td>30.3537</td>
</tr>
<tr>
<td>Couple</td>
<td>48.8620</td>
<td>26.8822</td>
</tr>
</tbody>
</table>

To appreciate the robustness of the proposed method against common attacks, the following experiments were performed on Lena image.

In Fig. 5, the response of the detector to watermarked image against JPEG compression is plotted. In Fig. 5 (a), the watermarked image is JPEG compressed with quality factor of 50 and in Fig. 5 (b), the quality factor is 25. The responses of the watermark detector in both cases are well above random, which suggest that the algorithm has great robustness towards lossy compression.

Fig. 6 (a) illustrates the watermarked image after noise addition whereas Fig. 6(b) shows median filtering copy. The detector responses to these kinds of attack are shown in Fig. 6(c) and (d). The embedded watermarks are detectable in both cases, showing that the algorithm is robust to both kinds of attacks.

The proposed method is quite immune to Gaussian blur, as Fig. 7(a) (c) shows. Finally, the robustness of the proposed method against cropping is examined. In Fig. 7(b), the response of the watermark is still has been removed.

6. Conclusions

In this paper, a novel algorithm for image watermarking has been presented. The method exploits a perceptual model based on NVF and it embeds the watermark data on selected wavelet coefficients of the original image. Experimental results illustrate that the proposed method is well adapted to various types of
images. The evaluation of the method shows very good performance as far as transparency and robustness is concerned. The proposed scheme behaves very well in various common image processing operations such as compression, filtering, noise addition, blurring and cropping.

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References


(a) Gaussian Blur                                    (b) 1/4 cropped

(c)Detector Response to (a)                          (d) Detector Response to (b)

Fig.7 Detector Response to Gaussian Blur and Cropping