A Multiresolution Watermark for Digital Images

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Abstract

In this paper, we introduce a new multiresolution watermarking method for digital images. The method is based on the discrete wavelet transform (DWT). Pseudo-random codes are added to the large coefficients at the high and middle frequency bands of the DWT of an image. It is shown that this method is more robust to often proposed methods to some common image distortions, such as the wavelet transform based image compression, and image halftoning. Moreover, the method is hierarchical. The computation load needed to detect the watermark depends on the noise level in an image.

1. Introduction

With the rapid development of the current information technology, electronic publishing, such as the distribution of digitized images/videos, is becoming more and more popular. An important issue for electronic publishing is copyright protection. Watermarking is one of the current copyright protection methods that have recently received considerable attention. See, for example, [1-8]. Basically, watermarking for digital images consists of signing an image with a signature or copyright message such that the message is secretly embedded in the image and there is no visible difference between the original and the signed images.

There are two common methods of watermarking: the frequency domain and the spatial domain watermarks, for example [1-8]. In this paper, we focus on frequency domain watermarks. Recent frequency domain watermarking methods are based on the discrete cosine transform (DCT), where pseudo-random sequences, such as M-sequences, are added to the DCT coefficients at the middle frequencies as signatures [2-3]. This approach, of course, matches the current image/video compression standards well, such as JPEG, MPEG1-2, etc. It is known that the wavelet image/video coding, such as embedded zero-tree wavelet (EZW) coding, has potential to be included in the up-coming image/video compression standards, such as JPEG2000 and MPEG4 due to its excellent performance in compression. Therefore, it is important to study watermarking methods in the wavelet transform domain.

In this paper, we propose a wavelet transform based watermarking method by adding pseudo-random codes to the large coefficients at the high and middle frequency bands of the discrete wavelet transform of an image. There are three *advantages* of this approach. The first advantage is that the watermarking method has multiresolution characteristics and is hierarchical. In the case when the received image is not distorted significantly, the cross correlations with the whole size of the image may not be necessary, and therefore much of the computational load can be saved. The second advantage lies in the following argument. It is usually true that the human eyes are not sensitive to the small changes in edges and textures of an image but is very sensitive to the small changes in the smooth parts of an image. With the DWT, the edges and textures are usually exploited very well in high frequency subands, such as HH, LH, HL etc. The large coefficients in these bands usually indicate edges in an image. Therefore, adding watermarks on these large coefficients is difficult for the human eyes to perceive. The third advantage is that this approach matches the emerging image/video compression standards. Our numerical results show that the watermarking method we propose is very robust to wavelet transform based image compressions, such as the embedded zero-tree wavelet (EZW) image compression scheme, and as well as to other common image distortions, such as additive noise, and halftoning.

2. Watermarking in the DWT Domain

The basic idea in the DWT for a one dimensional signal is the following. A signal is split into two parts of high frequencies and low frequencies. The part with the high frequencies is basically the edge components of the signal. The part with the low frequencies is split again into two parts of high and low frequencies. This process is continued an arbitrary number of times, which is usually determined by the application at hand. Furthermore, from these DWT coefficients, the original signal can be reconstructed. This reconstruction process is called the inverse DWT (IDWT). The DWT and IDWT for two dimensional images $x[m,n]$ can be similarly defined by implementing the one dimensional DWT and IDWT for each dimension m and n separately: $DWT_n[DWT_m[x[m,n]]]$. An image can be decomposed into a pyramid structure, shown in Fig. 1, with various band information: such as low-low frequency band, low-high frequency band, high-high frequency band etc.

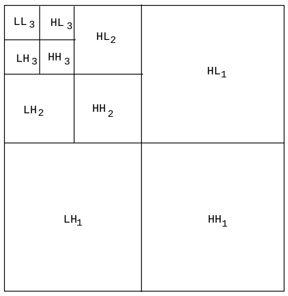

Figure 1: DWT pyramid decomposition of an image.

Watermarking in the DWT domain includes two parts: encoding and decoding. In the encoding part, we first decompose an image into several bands with a pyramid structure as shown in Figs. 1 and then add pseudo-random sequence (Gaussian noise) to the large coefficients which are not located in the lowest resolution, i.e., the corner at the left and top, as follows. Let $y[m,n]$ denote the DWT coefficients, which are not located at the lowest frequency band, of an image $x[n,m]$. We add a Gaussian noise $N[m,n]$ with mean 0 and variance 1 to $y[m,n]$:

$$\tilde{y}[m,n] = y[m,n] + \alpha(y[m,n])^2 N[m,n], \tag{1}$$

where α is a parameter to control the level of the watermark, the square ^{2} indicates the amplification of the large DWT coeffcients. We do not change the DWT coefficients at the lowest resolution. Then, we take the two dimensional IDWT of the modified DWT coefficients $\tilde{y}$ and the unchanged DWT coefficients at the lowest resolution. Let $\tilde{x}[m,n]$ denote the IDWT coefficients. For the resultant image to fit within the 0 to 255 integer values, typical image data, it is modified as

$$\hat{x}[m,n] = \lceil 255 \frac{\tilde{x}[m,n] - \min_{m,n}(\tilde{x}[m,n])}{\max_{m,n}(\tilde{x}[m,n] - \min_{m,n}(\tilde{x}[m,n]))} \rceil. \tag{2}$$

The operation in (2) is to make the two dimnsional data $\tilde{x}[m,n]$ be an 8 bit level image. The resultant image $\hat{x}[m,n]$ is the watermarked image of $x[m,n]$. The encoding part is illustrated in Fig. 2(a).

The decoding method we propose is hierarchical and described as follows. We first decompose a received image and the original image (it is assumed that the original image is known) with DWT into four bands, i.e., low-low (LL_1) band, low-high (LH_1) band, high-low (HL_1) band, and high-high (HH_1) band, respectively. We, then, compare the signature added in the HH_1 band and the difference of the DWT coefficients in HH_1 bands of the received and the original images by calculating their cross correlations. If there is a peak in the cross correlations, the signature is called detected. Otherwise, compare the signature added in the HH_1 and LH_1 bands with the difference of the DWT coefficients in the HH_1 and LH_1 bands, respectively. If there is a peak, the signature is detected. Otherwise, we consider the signature added in the HL_1, LH_1, and HH_1 bands. If there is still no peak in the cross correlations, we continue to decompose the original and the received signals in the LL_1 band into four additional subbands LL_2, LH_2, HL_2 and HH_2 and so on until a peak appears in the cross correlations. Otherwise, the signature can not be detected. The decoding method is illustrated in Fig. 2(b).

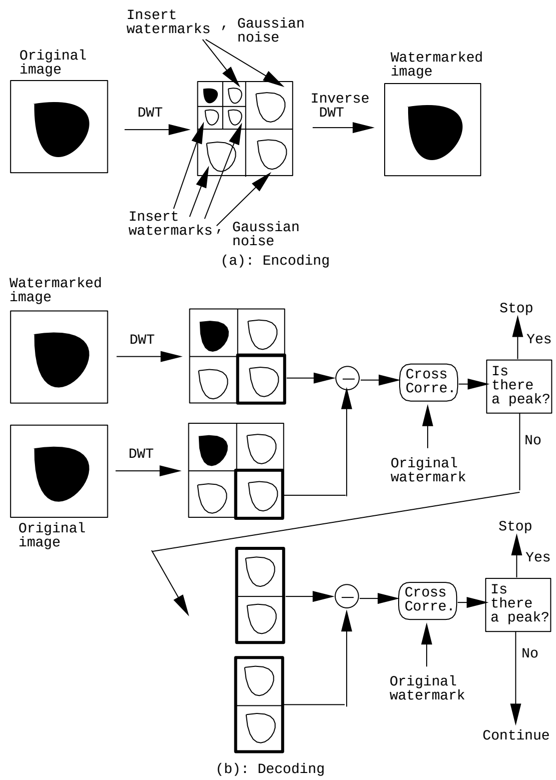

Figure 2: Watermarking in the DWT domain.

3. Numerical Examples

We consider the image "peppers" with size 512×512 shown in Fig. 3. We implement two watermarking methods: one is using the DCT approach proposed by Cox el. al. in [2] and the other is using the DWT approach proposed in this paper. In the DWT approach, the Haar DWT is used. Two step DWT is implemented and images are decomposed into 7 subbands. Watermarks, Gaussian noise, are added into all 6 subbands but not in the lowest subband (the lowest frequency components). In the DCT approach, watermarks (Gaussian noise) are added to the DCT coefficients at the same positions as the ones in the above DWT approach. The levels of watermarks in the DWT and DCT approaches are the same. Both watermarked images are indistinquishable from the original in our simulations.

The first distortion we test our algorithm with is additive noise. When the variance of the additive noise is not too large, the signature can be detected only using the information in the HH_1 band with the DWT approach, where the cross correlations are shown in Fig. 4(a) and a peak can be clearly seen. When the variance of the additive noise is large, the HH_1 band information is not good enough with the DWT approach, where the cross correlations are shown in Fig. 4(b) and no clear peak can be seen. However, the signature can be detected by using the information in the HH_1 and LH_1 bands with the DWT approach, where the cross correlations are shown in Fig. 4(d) and a peak can be clearly seen. For the second noisy image, we have also implemented the DCT approach. In this case, the signature with the DCT approach can not be detected, where the correlations are shown in Fig. 4(c) and no clear peak can be seen.

The second "test" distortion is image compression. Two watermarked images with the DWT and DCT approaches are compressed by using the EZW coding algorithm. The compression ratio is chosen as 64, i.e., $0.125bpp$. With these two compressed images, the correlations are shown in Fig. 5(a) and (b), where a peak in the middle can be clearly seen in Fig. 6(a) with the DWT approach, but no clear peaks can be seen in Fig. 5(b) with the DCT approach. This is not very surprising because the compression scheme is not suitable to the DCT approach.

The third "test" distortion is halftoning. The two watermarked images are both halftoned by using the following standard method. Let $x[m,n]$ be an image with 8 bit levels. To halftone it, we do the nonuniform thresholding through the Bayer's dither matrix T [9]:

$$T = (T_{j,k})_{4\times 4} = 16 \begin{pmatrix} 11 & 7 & 10 & 6 \\ 3 & 15 & 2 & 14 \\ 9 & 5 & 12 & 8 \\ 1 & 13 & 4 & 16 \end{pmatrix}$$

in the following way. Compare each disjoint 4×4 blocks in the image $x[m,n]$. If $x[m*4+j, n*4+k] \geq T_{j,k}$, then it is quantized to 1, and otherwise it is quantized to 0. Both DWT and DCT watermarking methods are tested. Surprisely, we found that the watermarking method based on DWT we proposed in this paper is more robust than the method based on the DCT in [2-3]. The correlations are shown in Fig. 6(a) and (b), where (a) corresponds to the DWT approach while (b) corresponds to the DCT approach. One can clearly see a peak in the middle in Fig. 6(a) while no any clear peak in the middle can be seen in Fig. 6(b).

4. Conclusion

In this paper, we have introduced a new multiresolution watermarking method using the discrete wavelet transform (DWT). In this method, Gaussian random noise is added to the large coefficients in the DWT domain. The decoding is hierarchical. If distortion of a watermarked image is not serious, only a few bands worth of information are needed to detect the signature and therefore computational load can be saved. We have also implemented numerical examples for several kinds of distortions, such as additive noise, compressed image with the wavelet approach such as the EZW, halftoning, and reduced resolution. It is found that the DWT based watermark approach we proposed in this paper is robust to all the above distortions while the DCT approach is not, in particular, to distortions, such as the compression, additive noise with large noise variance, and resolution reduction.

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Figure 3: Original "pepper" image.

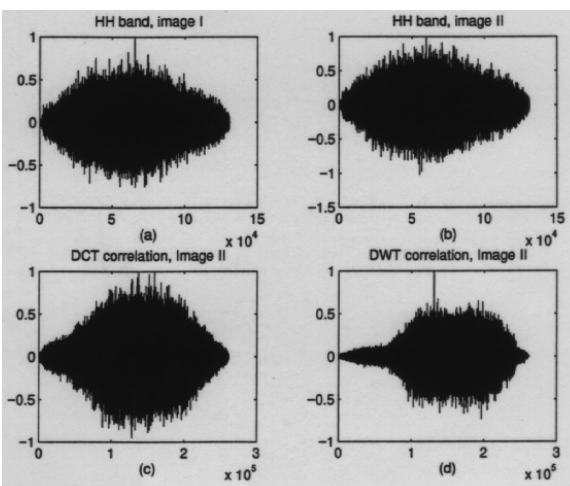

Figure 4: Correlations for watermark detection: (a) DWT with HH_1 band for low additive noise; (b) DWT with HH_1 band for high additive noise; (d) DWT with HH_1 and LH_1 bands for high additive noise; (c) DCT for high additive noise.

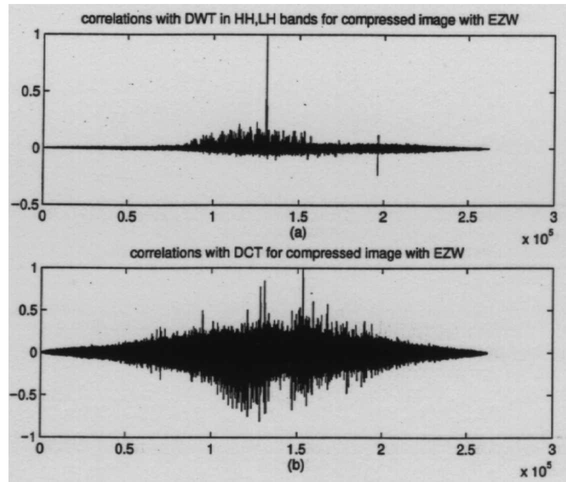

Figure 5: Correlations for watermark detection for compressed images: (a) DWT; (b) DCT.

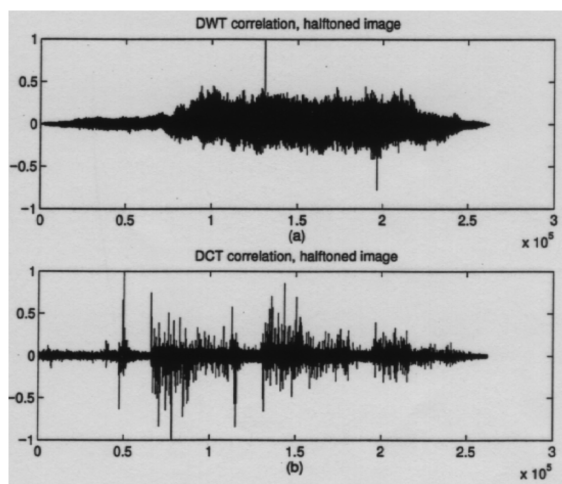

Figure 6: Correlations for watermark detection for halftoned images: (a) DWT; (b) DCT.