AN IMAGE-ADAPTIVE WATERMARK BASED ON A REDUNDANT WAVELET TRANSFORM

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ABSTRACT

In this paper, an image-adaptive watermarking technique based upon a redundant wavelet transform is proposed. The redundant transform provides an overcomplete representation of the image which facilitates the identification of significant image features via a simple correlation operation across scales. Although the watermarking algorithm is image adaptive, it is not necessary for the original image to be available for successful detection of the watermark. The performance and robustness of the proposed technique is tested by applying common image-processing operations such as filtering, requantization, and JPEG compression. A quantitative measure is proposed to objectify performance; under this measure, the proposed technique outperforms a wavelet scheme based on the usual critically sampled DWT.

1. INTRODUCTION

The rapid growth of the Internet makes communication easier and more extensive than before, while the advent of digital multimedia enables the creation and dissemination of products quickly via electronic means. These advances present a strong demand for the protection of intellectual-property rights for audio, video, images, and other documents. Image watermarking, an embedding of identification information into image data, is expected to play a very important role in the protection of copyrights on image data. The basic ideas behind image watermarking have emerged steadily over the last decade. Recently, there has been drastically increased interest from both academia and industry in this area, as witnessed by numerous patents filed for techniques for the protection of a broad array of multimedia products. Some international organizations are now considering combining watermarking techniques with already existing standards.

Most current image-watermarking research focuses on invisible watermarks, those which are imperceptible under normal viewing conditions. The different techniques that are used for invisible image watermarks can be categorized into two classes: spatial-domain watermarks and transform-domain watermarks [1]. The embedding of the image-watermark data into the least-significant bits of image pixels (e.g., [2]) is a typical approach employed by spatial-domain watermarking methods. For transform-domain techniques, an image transform, such as the discrete cosine transform (DCT) (e.g., [3-4]) or discrete wavelet transform (DWT) (e.g., [4-5]), is employed, the watermark is added to the transform coefficients, and the corresponding inverse transform is taken. As opposed to spatial-domain techniques which have relatively low bit capacity, transform-domain techniques can embed a large amount of watermark data without incurring noticeable visual artifacts, and they tend to be more robust than spatial-domain methods to attacks on the watermark [2].

In this paper, we present a transform-domain watermarking approach based upon the addition of watermark data to wavelet coefficients. Unlike other wavelet-based watermarking techniques which employ the usual critically sampled dyadic DWT widely used within the image-compression community, we employ instead a *redundant* wavelet transform which produces an over-complete, oversampled expansion system. As in the case of other techniques, notably the wavelet approach described in [4], our watermark is image-adaptive in that the strength of the watermarking is controlled by the significance of the image coefficients—the greater the significance of coefficient, the greater is the amount of watermark information embedded in it. As we describe below, the redundant transform we use facilitates the identification of coefficient significance; this significance information is collected in a mask for image-adaptive weighting of the watermark information. We note that, although our watermarking algorithm is image adaptive, it is not necessary for the original image to be available for successful detection of the watermark.

2. THE REDUNDANT WAVELET TRANSFORM

The redundant wavelet transform, or RDWT, that we employ in our watermarking technique is somewhat different from the traditional critically sampled dyadic image DWT. Whereas the critically sampled DWT is widely used in signal compression, the RDWT has been

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proposed for signal detection and enhancement [6,7], since the RDWT maintains uniform sampling rate in the time domain and is in some respects a discrete approximation to the continuous wavelet transform. In practice, the RDWT is implemented via the "algorithme à trous" [6]—in brief, instead of downsampling the lowpass signal during each filter-bank iteration as is done in the usual DWT, the filters themselves are upsampled before performing filter convolution at each scale.

The redundancy of the RDWT facilitates the identification of salient features in an image, especially image edges. Specifically, the direct multiplication of the RDWT coefficients at adjacent scales distinguishes important features from the background due to the fact that wavelet-coefficient magnitudes are correlated across scales. Coefficient-magnitude correlation is well known to exist in the usual critically sampled DWT also; however, the changing temporal sampling rate makes the calculation of an explicit correlation mask across scales much more difficult for the critically sampled DWT [7].

3. THE RDWT WATERMARKING ALGORITHM

The redundancy in the RDWT permits simple signal denoising using a correlation mask created by direct multiplication of subband signals [7]. To some extent, image watermarking can be viewed as the inverse process of image denoising—in image watermarking, the watermark, which can be consider as "noise," is added to the original image. The goal is that the added "noise" be invisible to the human visual system (HVS) and difficult to remove by intentional or non-intentional image operations. The RDWT aids the watermarking process by providing a mask to guide where the watermark is added.

In our technique, white Gaussian noise is used as a code sequence (the watermark); this noise is added to the RDWT coefficients of the image, according to:

$$\begin{aligned} f'_{\{V,H,D\}}(x,y) &= f_{\{V,H,D\}}(x,y) \\ &\quad + \alpha v_{\{V,H,D\}}(x,y) w_{\{V,H,D\}}(x,y) \end{aligned} \qquad (1)$$

where $f_{\{V,H,D\}}(x,y)$ are the RDWT coefficients of the image, $v_{\{V,H,D\}}(x,y)$ are the added watermarks, and V, H, and D stand for the vertical, horizontal, and diagonal components respectively. The parameter α controls the strength of the watermarks, and $w_{\{V,H,D\}}(x,y)$ are the correlation weighting masks for the vertical, horizontal, and diagonal components. Eq. 1 guarantees that the added watermark is robust by embedding it in the significant features of the image; the location of the significant features are given by the correlation mask. In our technique, the correlation mask is created as

$$w_{i\{V,H,D\}}(x,y) = \prod_{j=1}^{i} f^{*}_{j\{V,H,D\}}(x,y), \qquad (2)$$

where $f^{*}_{j\{V,H,D\}}$ are the normalized RDWT coefficients at scale j of the transform, i.e.,

$$f^{*}_{j\{V,H,D\}} = \frac{f_{j\{V,H,D\}}(x,y) \cdot f_{j\{V,H,D\}}(x,y)}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f_{j\{V,H,D\}}(x,y)^2}, \qquad (3)$$

and $w_{i\{V,H,D\}}(x,y)$ is the correlation mask obtained from scale 1 through scale i of the transform. We note that calculation of the correlation mask in this manner is possible due to the fact that each RDWT subband is the same size as the original image.

The detection of the existence of the watermark is simply an inverse process. That is, after taking the RDWT of the image, a simple correlation method is used to detect the similarity and identify the watermark. Specifically, the similarity is

$$\rho = \max_{\{S=V,H,D\}}[\rho_S], \qquad (4)$$

where

$$\rho_S = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f'_S(x,y) v_S(x,y) \qquad (5)$$

is the similarity measure for subband s, $f'_S(x,y)$ are the RDWT coefficients of the image to be tested, and $v_S(x,y)$ are the watermarks added to the vertical, horizontal, or diagonal subbands. ρ corresponds to the maximum similarity coefficient from each of the different orientations, which makes our technique robust to attacks that affect the orientations differently [4]. Here, it is assumed that the image size is $M \times N$.

The above detection scheme does not require that the original image, $f_S(x,y)$, be available at the detector. However, if the original image can be used in detection, a modified similarity measure can be used in place of Eq. 5. That is,

$$\rho_S = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} [f'_S(x,y) - f_S(x,y)] v_S(x,y). \qquad (6)$$

provides similarity for subband s in this case, while Eq.4 is employed unchanged.

4. EXPERIMENTAL RESULTS

For the experimental results described in this section, our RDWT watermarking technique employs a two-scale, separable 2D RDWT using length-4 Daubechies wavelet filters. Coefficients of the first scale (highest-frequency H, V, and D subbands) are watermarked, while the mask

$w_{\{V,H,D\}}(x,y)$ is obtained from multiplying the appropriate subbands from both scales. The parameter α that controls the strength of the added watermark is selected so to achieve a given PSNR. We compare the performance of our RDWT technique to another technique by adjusting the strength of the watermarking so that the same PSNR is obtained for both techniques. Fig. 1 shows the masks $w_{\{V,H,D\}}(x,y)$ for lenna.

We compare our RDWT technique to another transform-domain technique intended to be representative of the typical approach based on the usual critically sampled DWT. Specifically, we use the approach proposed in [4], except that the subband weights, $w_{\{V,H,D\}}(x,y)$, are the just-noticeable distortion (JND) values tabulated in [8], which have been widely used in perceptually based image-compression applications. In this case, watermarking is equivalent to Eq. 1 except that the transform is now critically sampled and the subband weights are not image adaptive but are, rather, constant across each subband. Again, we use the length-4 Daubechies filter, and Eqs. 4 and 5 provide watermark detection.

In both techniques, the watermark strength is adjusted as needed to obtain a given PSNR (for these experiments, approximately 34dB for lenna). White Gaussian noise with zero mean and unit variance is used as the added watermark.

The detector responses for the two techniques are given in Fig. 2, wherein we have 1000 different watermarks, and the correct mark is mark 200. In order to give a quantitative measure of detection performance, we propose a "peak-response gain" measure which we define as

$$G = N * \{\max_n [\rho(n)]\}^2 / \sum_{n=1}^{N} \rho(n)^2 \qquad (6)$$

where $\rho(n)$ is the detector response for trial n and N is the number of total trials. This peak-response gain gives a measure of how large the detector response to the correct mark is in relation to the average response for incorrect marks. This measure provides an indication of how difficult it is to detect the correct-mark peak—the larger the peak-response gain, the easier it is to set a threshold for mark detection. Table 1(a) shows the peak-response gains for the RDWT and DWT techniques.

The robustness of the watermarking techniques is tested through general image processing methods such as lowpass filtering (5×5 spatial averaging), requantization (8-level uniform scalar quantization), and lossy compression (JPEG with a quality factor of 15). The peak-response gain performance for these degradation operations are shown for two techniques in Tables 1(b)-(d). We note that our RDWT technique consistently outperforms the DWT technique.

5. CONCLUSION

In this paper, an image-adaptive watermarking technique based on a redundant wavelet transform is presented. By using the direct product of the wavelet coefficients at different scales as a significance mask, this technique can embed the invisible watermark into salient features of the image thus ensuring robustness to subsequent image-processing operations that may be used to attack the watermark. A quantitative measure is proposed to objectify performance; under this measure, the proposed technique outperforms a wavelet scheme based on the usual critically sampled DWT.

6. REFERENCES

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Technique	PRG
DWT	835.6
RDWT	996.4

(a)

Technique	PRG
DWT	9.8
RDWT	147.9

(b)

Technique	PRG
DWT	827.1866
RDWT	994.6259

(c)

Technique	PRG
DWT	9.5228
RDWT	649.0675

(d)

Table 1. The peak-response gain (PRG) for the watermarked lenna image (a) without any operation, (b) with filtering, (c) with requantization, (d) with JPEG compression

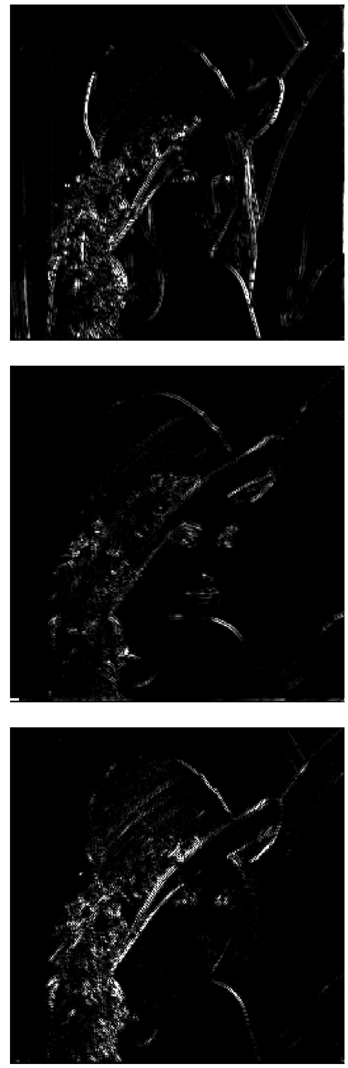
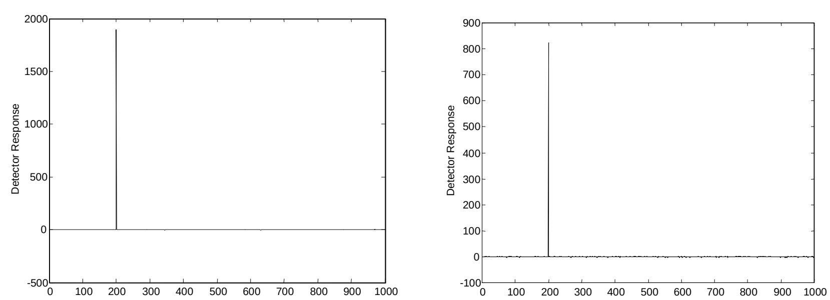


Figure 1. Correlation masks from the RDWT watermarking technique for lenna (vertical, horizontal, and diagonal masks, respectively, top to bottom)



(a) (b)

Figure 2.Detector response for watermarked lenna image (a) DWT, (b) RDWT

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