Image Watermarking using Hybrid Wavelets and Directional Filter Banks

Ramin Eslami and Hayder Radha

Abstract—We recently proposed a new family of nonredundant directional image transforms using *Hybrid Wavelets and Directional filter banks* (HWD). In this paper we develop and analyze an HWD family algorithm for blind multiplicative watermarking. We approximate the watermarked coefficients by a generalized Gaussian distribution probability model and use a locally optimal detector. Then, we compare the performance of the HWD family to that of wavelet-based image watermarking.

***Index Terms*—Directional filter banks, image watermarking, wavelet transform**

I. Introduction

It has been well established that the wavelet transform is not optimal in representing textures and fine details in images due to the lack of directionality. Under nonlinear approximation, we have shown [4] that a proposed family of *Hybrid Wavelets and Directional filter banks* (HWD) can achieve better visual performance in preserving textures and fine details than wavelets while reducing many of the artifacts that can be observed in smooth image regions when using directional transforms such as contourlets [4], [5].

In this paper we employ the HWD schemes for image watermarking applications. We also compare the performance of the proposed scheme with wavelet-based watermarking, which has been popular for transform-domain image watermarking. Further, we study watermarking using *Wavelet-based Contourlet Transform* (WBCT) [5]. Moreover, in our approach, we employ a locally optimal detector [1] in conjunction with a generalized Gaussian distribution model. Finally, our approach is partly motivated by spread spectrum methods, which have proven to be efficient methods for watermarking [3], [7]. Since spread spectrum approaches are based on embedding the watermark in the transform coefficients with large magnitude, we use the HWD family to embed the watermark mostly in edges where the human visual system is less sensitive. We show that this HWD-based watermarking attains better or comparable performance to that of the wavelet watermarking scheme.

R. Eslami and H. Radha are with the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48824 (phone: 517-432-9958; fax: 517-353-1980; e-mails: eslamira@egr.msu.edu *and* radha@egr.msu.edu).

II. Hybrid Wavelets and DFB (HWD) Schemes

Here we provide a brief description of the proposed *Hybrid Wavelets and DFB* (HWD) family. A detailed explanation can be found in [4]. To construct the HWD family, we proposed modified versions of the DFB, where we merely decompose the image into either *mostly vertical* or *mostly horizontal* directions, leading to the *Vertical DFB* (VDFB) or *Horizontal DFB* (HDFB), respectively. Now we add the feature of directionality to wavelets by applying the DFB and *modified* versions of the DFB to *some* of the finest scales. For the WBCT scheme [5], however, we applied the DFB to all the wavelet detail subbands in such a way to comply the anisotropic scaling law. We apply the (modified) DFBs to m_d, ($m_d < L$, L is the number of wavelet levels) finest scales of the wavelet subbands. We propose the following two types of the HWD family transforms:

1. HWD type 1
   a. apply the DFB to the m_d finest *diagonal* wavelet subbands (HH_i, $(1 \le i \le m_d)$),
   b. apply the VDFB to the m_d finest *vertical* wavelet subbands (HL_i, $(1 \le i \le m_d)$),
   c. apply the HDFB to the m_d finest *horizontal* wavelet subbands (LH_i, $(1 \le i \le m_d)$).
2. HWD type 2
   a. apply the DFB to the m_d finest *diagonal* wavelet subbands (HH_i, $(1 \le i \le m_d)$),
   b. apply the VDFB to the m_d finest *horizontal* wavelet subbands (LH_i, $(1 \le i \le m_d)$),
   c. apply the HDFB to the m_d finest *vertical* wavelet subbands (HL_i, $(1 \le i \le m_d)$).

In HWD1, we further directionally decompose the vertical and horizontal coefficients already obtained through wavelet filtering. We use the proposed modified versions of the DFB

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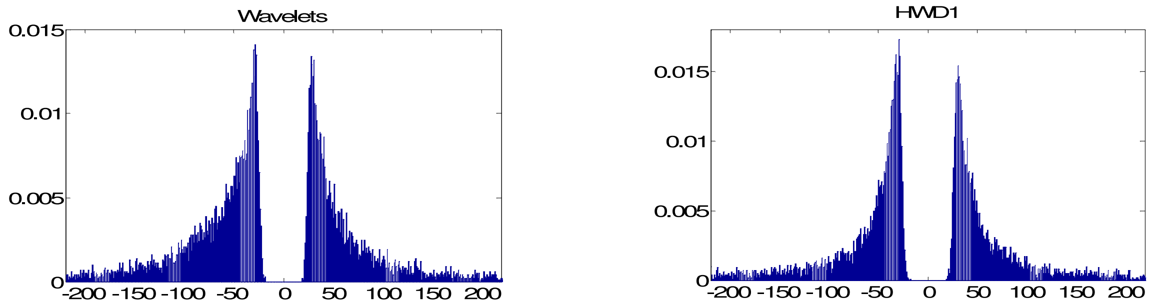

Fig. 1. Normalized histograms of the *Peppers* significant transform (detail) coefficients. *Left:* wavelets, *Right:* HWD1.

to lower the complexity and to further reduce the artifacts. In HWD2, however, we decompose the horizontal subbands vertically and the vertical subbands horizontally. Indeed, there are still horizontal (vertical) coefficients with low magnitude in the vertical (horizontal) subbands. One can boost these coefficients by applying the HDFB (VDFB) to these subbands and improve the directionality of wavelets. Since we apply the HDFB or VDFB to the coefficients with low magnitude, we expect fewer artifacts during nonlinear approximation. In both HWD1 and HWD2 we use DFB with D ($d = D/2$ for VDFB and HDFB) directions at $i = 1$, then we decrement the number of directions at every other levels.

III. Blind Watermarking

In this section we present an approach for applying the proposed HWD family and also the WBCT in image watermarking.

A. Locally Optimal Detector Using a Generalized Gaussian Distribution Probability Model

Here we consider multiplicative watermarking in which we follow the rule $z = x(1+\gamma w)$, where x is the input signal in the transform domain, w is the watermark signal, which we consider to be a white Gaussian noise with length equal to 10,000, and γ is the gain factor. As proposed in [3], [7], we embed the watermark in the perceptually most significant coefficients, hence, in the transform (*detail*) coefficients with high magnitude. We use $L = 5$ levels for all the schemes to avoid embedding the watermark in the coarser scales; because they represent low-frequency image components, where the watermark would become visible. For this study we consider a blind watermarking in which we have no access to the input signal x during watermark detection. We also suppose that the gain factor γ is unknown.

In [2] a *locally optimal* (LO) detector is proposed for multiplicative watermark detection when a *generalized Gaussian distribution* (GGD) probability model is assumed for the transform coefficients. In this work, however, we have to first analyze the HWD and also WBCT coefficients and fit them to a suitable probability model. Since we embed the watermark to the significant detail coefficients, we focus on

Table I. Parameter *c*, for the Significant Coefficients of the *Peppers*

Wavelet	HWD1	HWD2	WBCT
0.61	0.58	0.59	0.68

the histogram of these coefficients to find the desired probability model.

Fig. 1 shows the normalized histograms of the wavelet and HWD1 significant coefficients of the watermarked *Peppers* image as an example. As seen, there is a gap in the middle of the histograms, which is because we only consider significant coefficients in watermarking. In addition, the general shape of the HWD1 histogram is similar to that of wavelets. Despite the gap in these histograms, we consider a zero-mean GGD probability model as

$$p_X(x) = Ae^{-|\beta x|^c},$$

where $\beta = (1/\sigma)\left(\Gamma(3/c)/\Gamma(1/c)\right)^{1/2}$, and $A = \beta c/(2\Gamma(1/c))$.

The parameters are estimated as proposed in [1]. Table I shows the c parameters we obtained for the *Peppers* significant transform coefficients. As seen, the PDFs are neither Gaussian nor Laplacian, which justifies our selection of the GGD probability model.

For watermark detection, we use a *locally most powerful* (LMP) decision rule [6]. The hypotheses are

$$H_0: \ \gamma = 0, \quad \text{vs.} \quad H_1: \ \gamma > 0.$$

And the test statistic using an LMP rule is [6]

$$T_{LMP}(z) = \left.\frac{\partial \ln p(z,\gamma)}{\partial \gamma}\right|_{\gamma=0} \sqrt{\mathrm{I}^{-1}(\gamma = 0)},$$

where $\mathrm{I}(\gamma) = -E\left[d^2 p(z, H_1)/d\gamma^2\right]$ is the Fisher information matrix. Using this decision rule, we obtain an LO detector if the watermark magnitude is small compared with the signal magnitude. The PDF of the watermarked signal z, is computed as

$$p_Z(z) = \prod_i \frac{A}{1+\gamma w_i} e^{-\sum_i |\beta z_i/(1+\gamma w_i)|^c}.$$

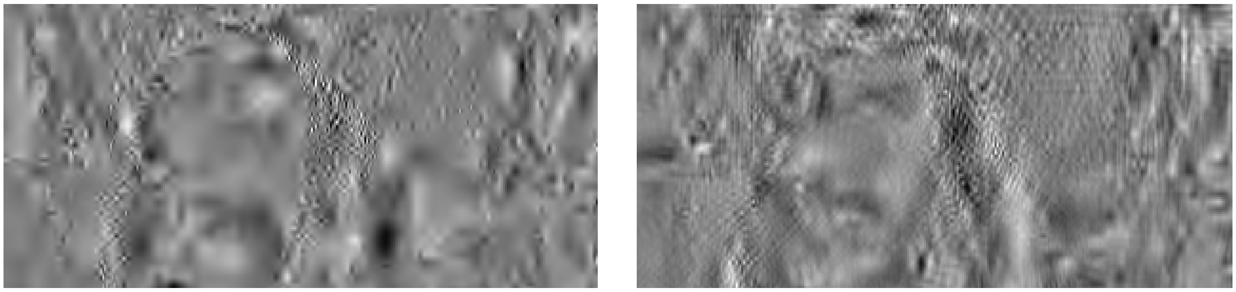

Fig. 2. The difference between watermarked and original *Barbara* images. *Left*: Wavelet scheme. *Right*. HWD1 scheme. (Part of the image is shown).

As a result, after some calculations $T_{LMP}(z)$ is found as

$$T_{LMP}(z) = \frac{\sum_i c w_i \mid \beta z_i \mid^c}{\sqrt{\sum_i (c(c+1) w_i^2 \mid \beta z_i \mid^c - w_i^2)}} .$$

Although we can approximately set $\sum_i w_i^2$ to N (number of watermark coefficients), for better detection performance we do not use this approximation.

B. Monte Carlo Experiments

We performed Monte Carlo experiments to evaluate the proposed watermarking scheme. We generated 400 pseudo-random white Gaussian noise sequences and embedded one sequence at each time to the significant transform coefficients. Then we evaluated the test statistic by applying all watermark sequences (one at each time), for a varying threshold, to draw the *receiver operating characteristic* (ROC) curve. Notably, we estimate the GGD parameters at each time we embed a watermark sequence. We watermarked two images *Peppers* and *Barbara* and used a gain factor equal to $\gamma = 0.1$, where the watermark is invisible.

Fig. 2 depicts the difference image between watermarked and original *Barbara* images for wavelets and HWD1 schemes. It can be seen that the watermark in the HWD1 scheme is more spread in the textures and edges when compared with the wavelet approach. Consequently, the HWD family and WBCT are more capable in spreading the watermark in images, while they still provide invisibility.

To compare the schemes, we lowered γ to 0.05 and obtained the ROC curves shown in Fig. 3. We see that by using a GGD model in combination with an LO detector, we usually attain better detection performance in the HWD and WBCT domains.

We also computed the ROC curves after JPEG compression attack. In this case, after embedding each watermark sequence with $\gamma = 0.1$, we compressed the resulting watermarked image with a quality factor of 5 (for higher qualities all schemes have perfect or near perfect performance) and performed a Monte Carlo experiment. Despite this low quality factor, our watermarking schemes provide high robustness.

Fig. 4 shows the resulting ROC curves. For the *Peppers* image, the HWD1 and WBCT schemes perform better and HWD2 is comparable to the wavelet scheme. However, for the *Barbara* image, the HWD and WBCT schemes have slightly lower performance than the wavelet approach. That is because the JPEG compression degrades many fine textures and details that are salient in the *Barbara* image. Therefore, it destroys some watermarked coefficients in the HWD and WBCT domains. For a piece-wise smooth image such as "*Peppers*", however, the salient features are edges, which can survive in JPEG compression.

IV. CONCLUSION

In this paper we employed our proposed HWD image transforms to image watermarking. We provided our preliminary work on blind watermarking using the proposed HWD family and also the WBCT, where we found them usually better or comparable to the wavelet watermarking scheme.

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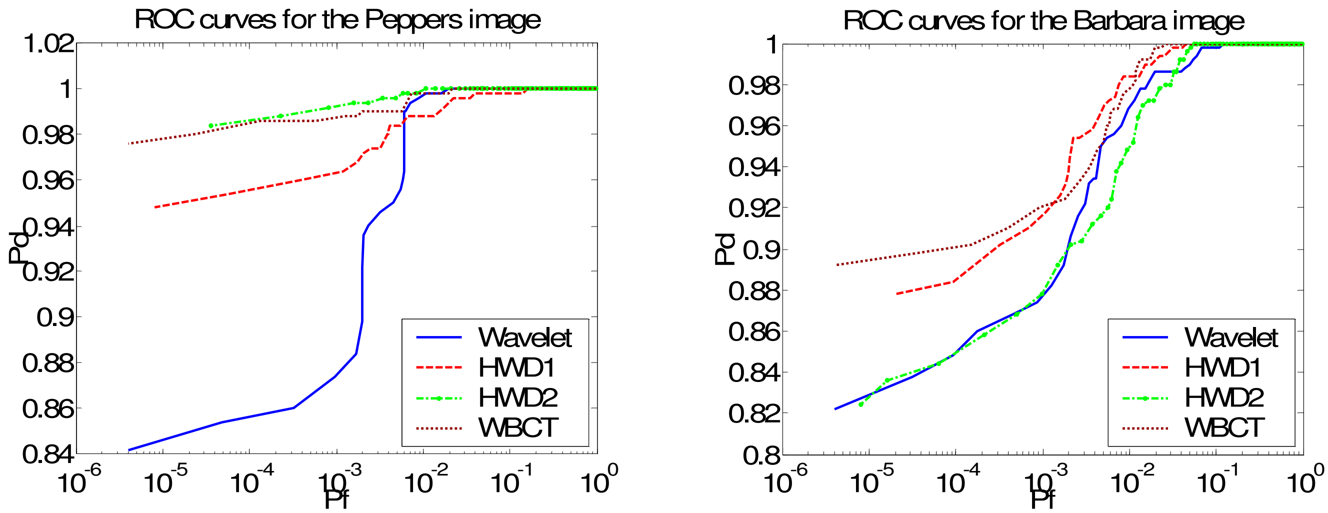

Fig. 3. ROC curves for the wavelets, WBCT, and HWD family schemes.

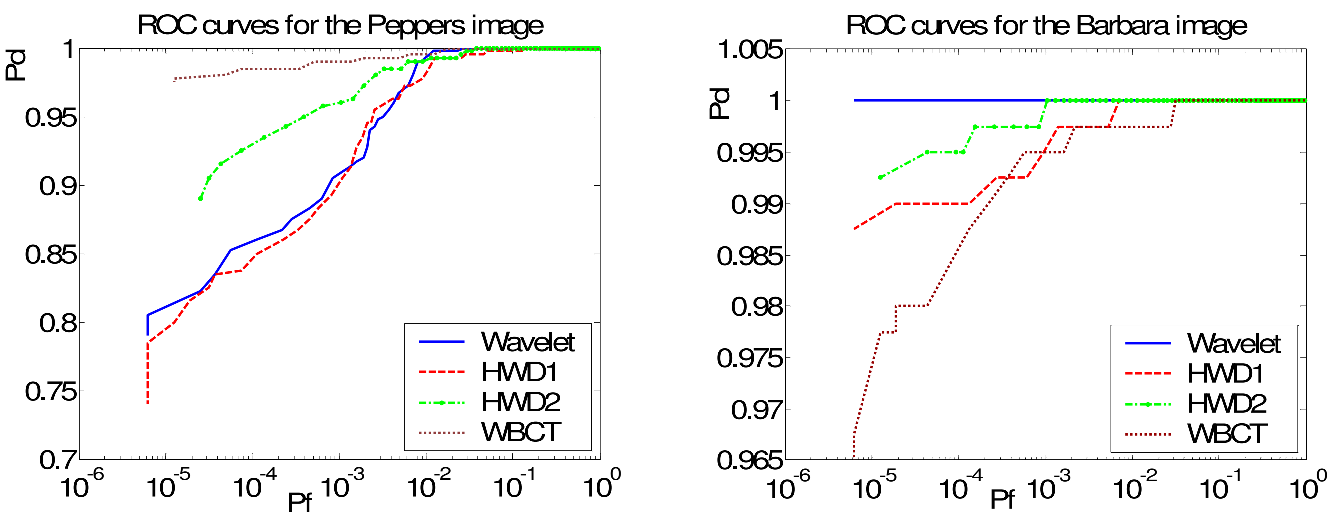

Fig. 4. ROC curves after JPEG compression with quality factor equal to 5.