Detection for Multiplicative Watermarking in DCT Domain by Cauchy Model

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Abstract. In the last decade, the requirement for copyright protection of digital multimedia has become more and more urgent. As an efficient method to address this issue, watermarking has gained a lot of attention. To watermarking system, detectors have an important influence on its performance. In this paper, we propose a new optimal detector to multiplicative watermarking in the discrete cosine transform (DCT) domain, which is based on Cauchy models. Furthermore, theoretical analysis is also presented. The performance of the new detector is confirmed by various experiments.

Keywords: Image watermarking, optimal detector, Cauchy distribution.

1 Introduction

Technology of watermarking has emerged as the digital data security and copyright protection issues has become increasingly important during last few years [1,2]. The basic principle of watermarking is to hide a specific information into a host data (e.g. image, audio, text, etc.) that it is intended to protect. The embedded information can be recovered or detected in the receiving end in order to verify ownership or intellectual property rights.

Up to now, most of published watermark approaches can be divided into two categories according to the different domains that watermark information is embedded: 1) spatial or time domain methods and 2) transform domain methods. Spatial domain methods are not popular for the reason that it can hardly maintain imperceptibility after information embedding, and it also relatively weak to intentional or unintentional attacks, such as filtering, compression, cropping and so on. On the contrary, transform domain methods could easily achieve good transparency of original works by exploiting characteristics of human visual system (HVS). Meanwhile it is robust to many digital data manipulations.

In order to verify the rightful ownership of a digital work, detection of the watermark is necessary. If the original image is available in receiving end, detection becomes simple. But in many real applications such as data monitoring

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or tracking, the original data is not always available, as a result, most of published literatures are concerned with design of blind detectors, which means the original host data is not required during the detection process. The most commonly used detector is the correlation detector, which is optimal only if the host data follows Gaussian distribution [3]. According to signal detection theory, the model of original data is very important and has a crucial influence on the performance of a detector. Since DCT domain coefficients are far from Gaussian distribution, correlation detector can hardly optimal nor robust. As a result, various literatures have considered DCT coefficients with more accurate models to improve the performance of watermark detectors. To additive watermarks, different probability density functions (PDF) have been used, such as generalized Gaussian(GG) and Laplacian [4] to DCT domain coefficients, Laplacian [5], student-t [6], modified Gauss-Hermite (MGD)[7] and NIG [8] to DWT domain coefficients. To multiplicative watermarks, a robust optimum detector in DCT, DWT and DFT domain is proposed by applying generalized Gaussian(GG) and Weibull distribution in [9]. In [10], the locally optimum detector for Barni's multiplicative watermarking scheme is proposed.

Since multiplicative watermarks are robust and suitable for copyright protection, this paper presents our investigation on robust optimum detection of multiplicative watermarks in DCT domain. The low- and mid-frequency DCT coefficients are modeled by Cauchy PDF, originally proposed in [11]. Furthermore, theoretical analysis of the detector is developed. Extensive experiments are carried out to demonstrate the performance of the proposed detector.

2 Multiplicative Watermarking Embedding Process

In this section, we briefly describe the multiplicative watermark embedding procedure in DCT domain [12]. Specifically, consider an image $\mathbf{f}$ in the spatial domain, whose pixels are denoted by $f(i,j)$. Let $\mathbf{x} = \{x_1, x_2, \ldots, x_N\}$ be a set of N host data, each element in$\mathbf{x}$, e.g. $x_i(i = 1, 2, \ldots, N)$, denotes the DCT transform coefficient of original image $\mathbf{f}$. We will apply the DCT transform in blocks of pixels, as in the JPEG standard. We represent watermark signal as $\mathbf{w} = \{w_1, w_2, \ldots, w_N\}$, then the commonly used multiplicative watermark embedding rule is:

$$y_i = x_i(1 + \alpha w_i) \qquad i = 1, 2, \ldots, N \tag{1}$$

where y_i is the sequence of watermarked signal, and α is an amplitude parameter which corresponds to a watermark power. α can be decided in two ways, one is the deterministic method which means α is set to be a specific value that is usually much smaller than 1.0 in multiplicative watermarks to keep the watermark imperceptible. The other method is to select α adaptively according to each subband DCT coefficients. For simplicity, in this paper, we set α to a specific value.

3 Proposed Watermark Detector

In general, most copyright protection applications contain a known watermark that is available both to the sender and receiver. Hence, the verification of existence, i.e. the detection of the watermark, is sufficient. Similar to signal detection problem in communications, watermark signal is regarded as the desired signal and host image data play the role of unknown noise. Thus, the verification of the existence of watermark in DCT coefficients of an image can be formulated as a binary hypothesis test given by

$$\begin{array}{l} H_0 : y_i = x_i \\ H_1 : y_i = x_i(1 + \alpha \cdot w_i) \end{array} \tag{2}$$

where two hypotheses are established, i.e. the null and the alternative hypotheses, corresponding to the existence and non-existence of the watermark, respectively. Based on Neyman-Pearson criterion, the decision rule of watermark detection can be formulated as follows:

$$\Lambda(\mathbf{Y}) \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{3}$$

where η is the decision threshold, it is selected by the rule that minimizes the probability of miss-detection for a bounded false alarm probability. $\Lambda(\mathbf{Y})$ is the likelihood ratio defined as

$$\Lambda(\mathbf{Y}) = \frac{p(\mathbf{Y}|H_1)}{p(\mathbf{Y}|H_0)} \tag{4}$$

This ratio is often simplified by taking natural logarithm, which leads to

$$l(\mathbf{Y}) = \ln\left(\frac{p(\mathbf{Y}|H_1)}{p(\mathbf{Y}|H_0)}\right) \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{5}$$

In order to obtain an optimal detector, an accurate model to the statistical characteristics of the DCT coefficients is crucial, the more accuracy of the model, the higher performance of the detector. In previous literatures, Laplacian and generalized Gaussian distribution (GGD) have often been used to characterize the data. But as pointed out in [4], even the GGD, are not appropriate for DCT coefficients, as they exhibit heavier tails than GGD can describe. In this paper, we model original data by Cauchy distribution, as this PDF shows heavier tails than GGD, and meets with the feature of DCT subband coefficients [13]. The PDF of Cauchy distribution is as follows

$$p_{\mathbf{X}}(x) = \frac{1}{\pi} \frac{\gamma}{\gamma^2 + (x - \delta)^2} \tag{6}$$

where γ is the data dispersion and δ is the location parameter. In order to attain the statistical decision function in (5), the two PDFs under both hypotheses H_0

and H_1 are required. From above discussion, we know that the low- and mid-frequency DCT coefficients of original image follow Cauchy distribution, to get PDF of watermarked data y_i, two assumptions are provided.

Assumption 1: y_i are i.i.d random variables.

Assumption 2: y_i follows the same distribution as x_i, i.e. Cauchy distribution, but has different parameters.

The first assumption comes from the fact that DCT transform approximates Karhunen-Loeve transform, and the second assumption lies in that usually the embedding strength is much smaller than 1 to keep the imperceptibility requirement of watermarked image.

Combined with assumption 1,2 and (5)(6), we can attain the optimal decision rule

$$\begin{aligned} l(\mathbf{Y}) &= \ln\left(\frac{p(\mathbf{Y}|H_1)}{p(\mathbf{Y}|H_0)}\right) = \ln\left(\frac{\prod_{i=1}^{N}\frac{1}{1+\alpha w_i}p_{\mathbf{X}}(\frac{y_i}{1+\alpha w_i})}{\prod_{i=1}^{N}p_{\mathbf{X}}(y_i)}\right) \\ &= \ln\left(\frac{\prod_{i=1}^{N}\frac{1}{\pi}\frac{\gamma}{\gamma^2+(\frac{y_i}{1+\alpha w_i}-\delta)}\frac{1}{1+\alpha w_i}}{\prod_{i=1}^{N}\frac{1}{\pi}\frac{\gamma}{\gamma^2+(y_i-\delta)^2}}\right) \\ &= \sum_{i=1}^{N}\ln\left(\frac{(1+\alpha w_i)(\gamma^2+(y_i-\delta)^2)}{\gamma^2(1+\alpha w_i)^2+(y_i-(1+\alpha w_i)\delta)^2}\right) \end{aligned} \tag{7}$$

where N is the number of subband coefficients to be watermarked.

4 Performance Analysis

Based on Neyman-Pearson criterion, the performance of the detectors can be measured by the probability of detection ($p_{\det}$) under a given probability of false alarm (p_{fa}). The probability of false alarm is

$$\begin{aligned} p_{fa} &= \Pr\left(l\left(\mathbf{Y}\right)|H_0 > \eta\right) \\ &= Q\left(\frac{\eta-m_0}{\sigma_0}\right) \end{aligned} \tag{8}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{+\infty} e^{-t^2/2}dt$, m_0 is the mean and σ_0^2 is the variance of $l(\mathbf{Y})$ under hypothesis H_0, respectively.

The detection probability is

$$\begin{aligned} p_{\det} &= \Pr\left(l\left(\mathbf{Y}\right)|H_1 > \eta\right) \\ &= Q\left(\frac{\eta-m_1}{\sigma_1}\right) \\ &= Q\left(\frac{m_0-m_1+\sigma_0 Q^{-1}(P_{fa})}{\sigma_1}\right) \end{aligned} \tag{9}$$

where m_1 is the mean and σ_1^2 is the variance of $l(\mathbf{Y})$ under hypothesis H_1, respectively. Therefore, the theoretical performance to a detector can be determined by m_0, m_1, σ_0 and σ_1. To the proposed detector, these parameters are estimated as follows

$$m_0 = \sum_{i=1}^{N}\ln\frac{(1-\alpha)^{1/2}(\gamma^2+(x_i-\delta)^2)}{x_1 x_2} \tag{10}$$

$$m_1 = \sum_{i=1}^{N} \ln \frac{(1-\alpha^2)^{1/2}}{x_3 x_4} \tag{11}$$

$$\sigma_0^2 = \sum_{i=1}^{N} \frac{1}{2} \left[\ln^2 \frac{(1+\alpha)x_2}{(1-\alpha^2)^{1/2}x_1} + \ln^2 \frac{(1-\alpha)x_1}{(1-\alpha^2)^{1/2}x_2} \right] \tag{12}$$

$$\sigma_1^2 = \sum_{i=1}^{N} \frac{1}{2} \left[\ln^2 \left(\frac{1+\alpha}{(1-\alpha^2)^{1/2}} \frac{x_4}{x_3} \right) + \ln^2 \left(\frac{1-\alpha}{(1-\alpha^2)^{1/2}} \frac{x_3}{x_4} \right) \right] \tag{13}$$

where

$$x_1 = \left[\gamma^2 (1+\alpha)^2 + (x_i - (1+\alpha)\delta)^2 \right]^{1/2} \tag{14}$$

$$x_2 = \left[\gamma^2 (1-\alpha)^2 + (x_i - (1-\alpha)\delta)^2 \right]^{1/2} \tag{15}$$

$$x_3 = \left\{ \frac{\gamma^2 (1+\alpha)^2 + \left[(x_i(1+\alpha) - (1+\alpha)\delta)^2 \right]^2}{\gamma^2 + [x_i(1+\alpha) - \delta]^2} \right\}^{1/2} \tag{16}$$

$$x_4 = \left\{ \frac{\gamma^2 (1-\alpha)^2 + \left[(x_i(1-\alpha) - (1-\alpha)\delta)^2 \right]^2}{\gamma^2 + [x_i(1-\alpha) - \delta]^2} \right\}^{1/2} \tag{17}$$

5 Experimental Results

In order to verify the superiority of the new detector proposed in this paper, we conduct several experiments with various actual images. Due to space limitation, here we only demonstrate the results for "Lena" and "Peppers" of size 512×512. The image is transformed by 8×8 block-wise DCT, and low- and mid-frequency coefficients are selected out to be embedded with watermark. Watermark signal **w** is generated by a pseudorandom sequence (PRS) generator, which takes the value of $+1$ and -1 with equal probability, that is $\sum_{i=1}^{N} w_i = 0$. To quantify the detection performance, the receiver operating characteristics (ROC) curves are plotted.

In our experiments, multiplicative watermark embedding rule of section 2 is used. Monte Carlo tests are conducted to experimentally validate the estimated ROC. Embedding strength α is fixed to a specific value much smaller than 1, for larger α, ROC curves are all straight lines with detection probabilities all equal to 1. The effectiveness of different detection schemes is compared with different "Watermark to Document Ratio" (WDR), which is defined as

$$WDR = 10 \log \left(\frac{\sigma_w^2}{\sigma_x^2} \right) \tag{18}$$

where σ_w^2 is the variance of watermark signal and σ_x^2 is the variance of original DCT coefficients, respectively.

5.1 Performance Comparison of Different Detectors

In this set of experiments, three different detectors, i.e. Cauchy, GG and Laplacian detector, are implemented to make a comparison of their effectiveness. Cauchy detector is derived by (7), GG and Laplacian detectors are from literature [9]. To get ROCs, the probability of false alarm is set from 10^{-4} to 1, to each p_{fa}, the threshold is computed by (8), then the likelihood ratio $l(\mathbf{Y})$ under hypothesis H_1 is empirically estimated and this value is compared to corresponding threshold. If it is above the threshold, the watermark is detected.

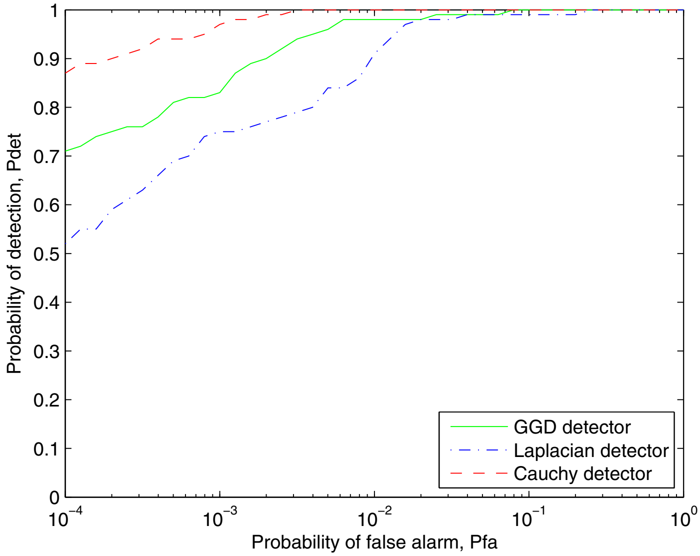
Fig. 1 shows the ROCs to image "Lena" and "Peppers". It is obvious that under the same p_{fa}, p_{det} of the proposed detector is much higher than that of the GG and Laplacian detectors, which meets with the fact that the Cauchy distribution is most appropriate for modeling the DCT data. Therefore the proposed detector is superior to the previous ones.

5.2 Empirical and Theoretical ROC

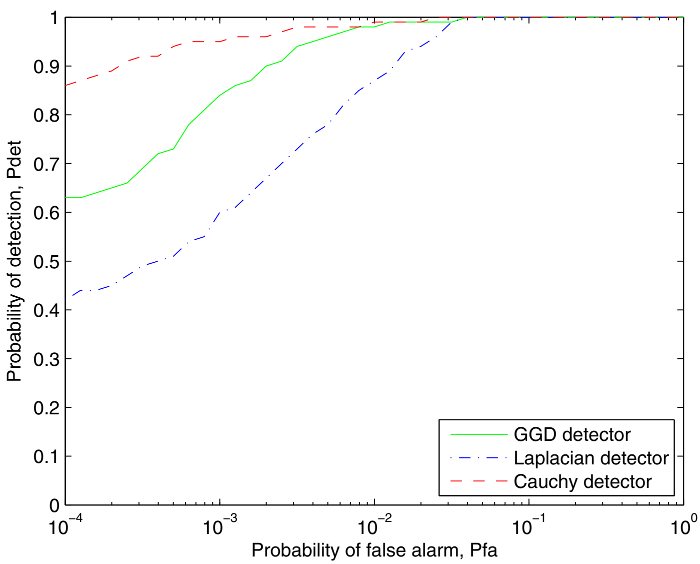
We also conduct experiments to verify the accuracy of theoretical analysis derived in section 4, with a specific embedding strength $\alpha = 0.08$. The analytical mean and variance of the detector can be directly computed from the data via (10)-(13), and by (9) we can get the theoretical ROC. The empirical ROC is plotted from the simulations mentioned above. Both ROCs are demonstrated in Fig. 2. From Fig. 2(a),(b), it can be seen that the empirical performance and theoretical one are in good agreement, therefore the correctness of our theoretical analysis can be confirmed.

5.3 Detection Performance of Different WDR

In order to compare the performance of the three detectors for different watermark strength, we carry out this set of experiments. The embedding strength is measured by WDR, as defined by (18). To our test images, WDR varies from -53dB to -42dB. Here, we consider the case that the probability of false alarm is fixed while measuring the corresponding probability of detection. In our tests, the probability of false alarm is set to 10^{-3}. The results are demonstrated by Fig. 3. It can be observed that the probability of detection increases with the strength of embedded watermark increases for all detectors. This is in line with intuitive sense, that the higher power of embedded signal, the easier to detect it. On the other side, we can find that the performance of Cauchy detector is better than that of the GG and Laplacian detector under any WDR.



(a)



(b)

Fig. 1. Empirical ROC curves of GGD, Laplacian and Cauchy detectors. (a)Lena. (b)Peppers.

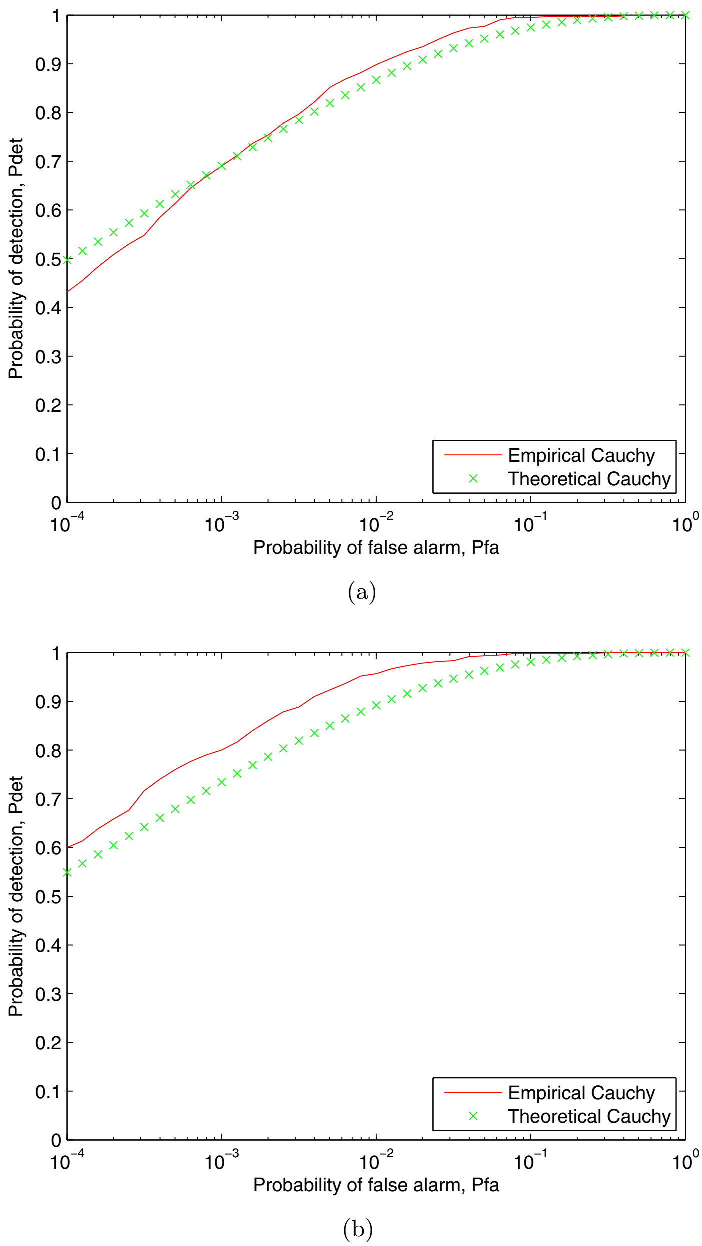
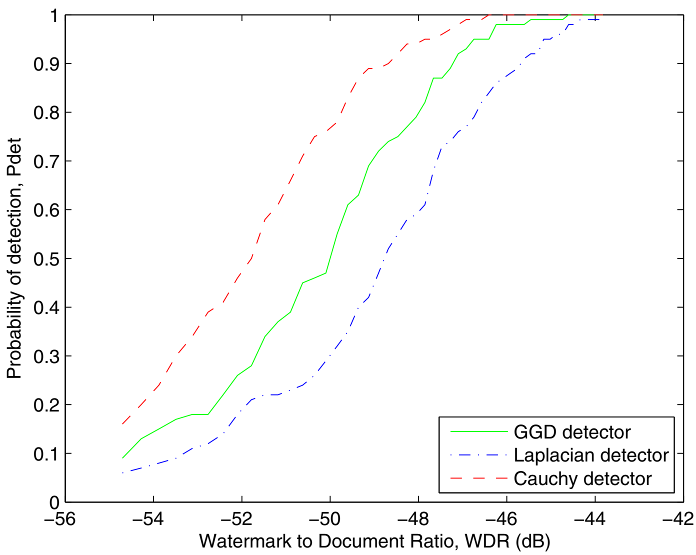
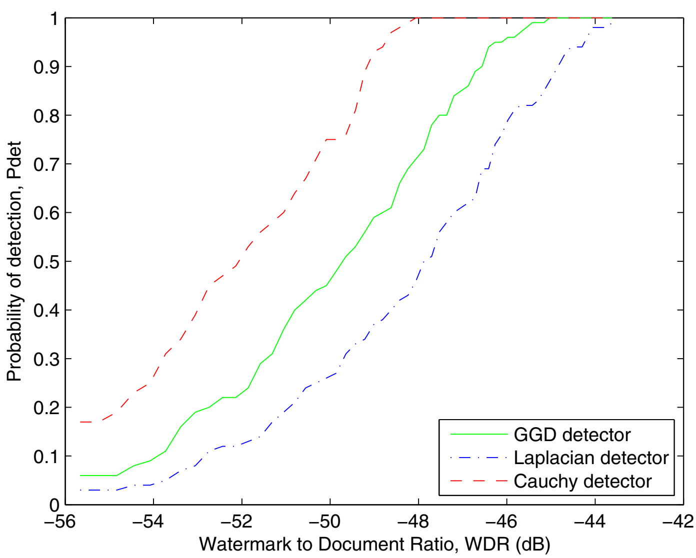


Fig. 2. Empirical and theoretical ROC curves. (a)Lena. (b)Peppers.



(a)



(b)

Fig. 3. ROC curves of different WDR. (a)Lena. (b)Peppers.

6 Conclusion

In this paper, a novel detector for the DCT-based multiplicative watermarking scheme is proposed by modeling the data with Cauchy distribution, which is more appropriate to describe the heavy-tailed characteristics of DCT coefficients. The theoretical performance of the detector has also been derived. The experimental results have validated the correctness of theoretical analysis and shown superior performance of the newly developed detector over that of conventional GG and Laplacian detector.

We note that in [14,15], a locally most powerful detector to multiplicative watermark in curvelet domain is developed, in which GGD, Laplacian distribution and Cauchy distribution are used to model the coefficients, respectively. They conclude that detector based on Cauchy distribution has superior performance, which is similar to our work. But we argue that compared with curvelet transform, DCT is easier to implement and more widely used in image processing, especially in image compression, therefore our method has more application in real practice.

In this paper, attacks to detectors are not considered, such as geometrical attacks, compression, coding and so on. As a important measure index to a detector, the robustness of our scheme will be the focus of research in the future.

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