Locally optimum detection for additive watermarking in the DCT and DWT domains through non-Gaussian distributions

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Abstract—**This work presents a new locally optimal blind detector for the additive transform-based image watermarking problem. Working in non-Gaussian environments, we introduce a new statistical model and its consequent application in the design of a locally optimum detection test. More specifically, we model the marginal distributions of the detail subband coefficients of DWT (Discrete Wavelet Transform) or DCT (Discrete Cosine Transform) with Student-t distribution. Since the watermark signal has low power, locally most powerful (LMP) detector is a valid choice. The experimental results show that the proposed detector has superior performance than alternative LMP detectors based on known state of the art statistical models.**

Keywords—image watermarking, locally most powerful test, DWT, DCT, Student-t distribution

I. INTRODUCTION

Watermarking has received a lot of attention since it has been proved an effective framework for protection of digital media [1][2]. Thus, a watermarking procedure is accomplished by embedding an imperceptible information in host multimedia content without affecting the quality of original data. In addition, following blind watermarking, this secret information continues to be detectable without resorting to the unwatermarked host signal.

Watermark detection is a crucial part of a watermarking system and various optimal transform based methods have been proposed all these years [3]-[7]. Common image transforms in image watermarking are DWT, DCT, DFT (Discrete Fourier Transform) or other multiscale transforms [11]. Properties like multiresolution, HVS (Human Visual System) modeling or spatial adaptivity has been proved helpful for better information embedding, efficient watermark detection and in essence improved watermarking schemes [1], [2].

Generally speaking, transform coefficients are considered as channel noise and the hidden information is viewed as the signal to be transmitted through this channel. If we assume that coefficients of our interest obey in a Gaussian law, then linear-correlator detector, has been proved an optimal solution[1]-[5]. But, marginal distributions of DWT detail subband coefficients or DCT coefficients are non-Gaussian thus linear correlator has suboptimal behavior with regard to signal detection [3]-[5].

In previous years, various models have been developed to account for non-Gaussian behavior of image statistics. Image data statistics in transform domain are modeled following more heavy-tailed distribution leading to optimal or nearly optimal detectors which exploit the aforementioned characteristic. In the additive watermarking problem Generalized Gaussian Density (GGD) [3], [4] has been widely adopted all these years by many researchers. Cauchy distribution [5]-[7] as a member of SaS (Symmetric alpha Stable) distributions, has been an alternative solution applicable to the same problem. Recently, Student-t distribution has also been proposed in the same context [10]. In this work, within the framework of weak signal detection and additive spread spectrum embedding in both DCT and DWT domains, we propose a class of watermark detectors based on a locally most powerful test [6] using the Student-t distribution.

Basic motivations to choose t-distribution for the problem of watermarking is its ability of describing images with different statistical characteristics, the extraction of a simple test statistic and the efficient detection sensitivity compared to other known state of the art detectors, which are based on known statistical distributions. Thus, in case of Student-t we expect that the nonlinear preprocessor will provide us with high detection sensitivity and improved robustness. The model depends on two parameters which can be estimated quickly and easily whereas the whole procedure may become more relaxed if we fix them providing a more light version of the proposed detectors.

This work is organized as follows. The next section defines the known additive watermarking detection problem. Section III proposes the new statistical model where the domains of embedding and detection are described in Section IV. Section V presents the experimental results and the final section gives the conclusions.

II. ADDITIVE WATERMARKING DETECTION PROBLEM

Assuming that we embed the watermark information $\mathbf{W} = \{\mathbf{W}[1],...,\mathbf{W}[N]\}$ in an additive way, then the N host transform coefficients $\mathbf{X} = \{\mathbf{X}[1],...,\mathbf{X}[N]\}$ become $\mathbf{Y} = \{\mathbf{Y}[1],...,\mathbf{Y}[N]\}$. Watermark detection can be stated as a binary hypothesis problem where in the viewpoint of statistical detection theory [16], [21]:

$$\begin{aligned} &H_1 : \mathbf{Y}[i] = \mathbf{X}[i] + \alpha \mathbf{W}[i] \\ &H_0 : \mathbf{Y}[i] = \mathbf{X}[i] \end{aligned} \tag{1}$$

where H_1 is the alternative hypothesis indicating the presence of hidden information and H_0 is the null hypothesis where no watermark is present. Index i denotes the transform coefficient location where the watermark is supposed to be embedded. Defining the likelihood ratio test and then taking the logarithm, the log-likelihood becomes:

$$l(\mathbf{Y}) = \sum_{i=1}^{N} \log\left[\frac{p_x(\mathbf{Y}[i] \mid H_1)}{p_x(\mathbf{Y}[i] \mid H_0)}\right] \tag{2}$$

where $p_x(\cdot)$ is the probability distribution function (pdf) for the problem at hand (noise distribution). The above test is performed using N transform coefficients which are treated as independent identically distributed (i.i.d) random variables.

Knowing that a UMP (Uniform Most Powerful) test is quite rare for non-Gaussian noise models, in this work we propose a Locally Most Powerful (LMP) test, achieving asymptotically optimum performance for watermark signals with low power level [4][6][16]. Based on the imperceptibility condition the magnitudes of hidden information $\mathbf{W}[i]$ are small, thus the appropriateness of an LMP test is valid. However, the watermarkÕs strength is unknown from the receiverÕs side. Instead of the simple hypothesis test in (1), we resort this to the following composite hypothesis testing [21]:

$$H_0 : \alpha = 0, \ vs \ H_1 : \alpha > 0 \tag{3}$$

The alternative hypothesis depends on the unknown watermark strengthÕs parameter and we seek for a test statistic which is optimal in the sense of LMP test. Therefore, detectorÕs sensitivity to watermarkÕs amplitude becomes even smaller.

For the log-likelihood in Eq. (2) the Taylor series approximation gives:

$$l(\mathbf{Y}[i])\Big|_{W\{i\}} = l(\mathbf{Y}[i])\Big|_{W[i]=0} + \left.\frac{\partial l(\mathbf{Y}[i])}{\partial \mathbf{Y}[i]}\right|_{W[i]=0} \cdot \mathbf{W}[i] + o(|\mathbf{W}[i]|) \tag{4}$$

Excluding the second and higher orders, is almost equal to:

$$\begin{aligned} l(\mathbf{Y}[i])\Big|_{\mathbf{W}\{i\}} &\cong -\frac{p_X'(\mathbf{Y}[i])}{p_X(\mathbf{Y}[i])} \cdot \mathbf{W}[i] + o(|\mathbf{W}[i]|) \\ &= g_{LO}(\mathbf{Y}[i])\,\mathbf{W}[i] \end{aligned} \tag{5}$$

where $g_{LO}(x)$ denotes the Òlocally optimum nonlinearityÓ as this described in [6].

III. Proposed Statistical Model

An important characteristic of the image statistics in wavelet or DCT domain is that it is non-Gaussian having a high kurtosis, sharp central peak and heavy tails [19]. Thus, various non-Gaussian pdfs have been proposed in the watermarking literature for modeling the transform coefficients [3]-[8]. In this work, we propose modeling of either marginal distribution of the subband coefficients in DWT [10] or coefficients of DCT transform with Student-t distribution. Student-t distribution is of central importance in statistical inference, since it offers a viable alternative with respect to real world images particularly because its tails are more realistic. The probability density function of Student-t is given by [9]:

$$St(\mathbf{X}(i) \mid 0, \lambda, \nu, \mu) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)}\left(\frac{\lambda}{\nu\pi}\right)^{\frac{1}{2}}\left(1 + \frac{\lambda}{\nu}(\mathbf{X}(i) - \mu)^2\right)^{-\frac{\nu+1}{2}} \tag{6}$$

In our case, mean value μ is supposed to be equal to zero. Parameter λ is usually called the ÒprecisionÓ of the t-distribution where ν is called the Òdegrees of freedomÓ In case ν is equal to 1 the t-distribution reduces to the Cauchy distribution, while in the limit $\nu \to \infty$, the t-distribution with zero mean, precision λ and degrees of freedom ν becomes a Gaussian with zero mean and precision λ . Notice that, Student-t distribution is obtained by adding up an infinite number of Gaussian distributions having the same mean but different precisions [15].

Compared with the Gaussian distribution, Students-t tails have slower decaying, hence we can describe a wider class of images regarding their statistical characteristics in the transform domain. Regarding the estimation of distributionÕs parameters, we find the Maximum Likelihood (ML) solution by invoking the EM (Expectation Maximization) algorithm as this described in [10], [13]. Notice that the pdf parameters can be estimated efficiently from the watermarked data instead of the original without any violation of test requirements [1], [2].

IV. Embedding And Detection Domains

Introducing the previous class of detectors, we consider these locally optimal detectors both in DCT and DWT domains. Both domains are widely applied in image and video processing areas, since they collect attractive features like fast algorithms, efficient implementations etc.

A. DCT domain

In case of DCT domain, our dataset of interest considers the set of non-DC coefficients. Many distributions such as Gaussian, Laplacian are proposed to describe the statistical distribution of this transform [1], [2], [12]. Although coefficients of low frequencies can not be approximated in an efficient manner by Gaussian or Laplacian distribution as depicted in works of [3], [19]. In the work of [3], [8] Generalized Gaussian has been proposed as an appropriate model for all DCT coefficients except DC. This fact led many researchers to investigate alternative statistical models capable of providing more efficient detectors in the watermarking field.

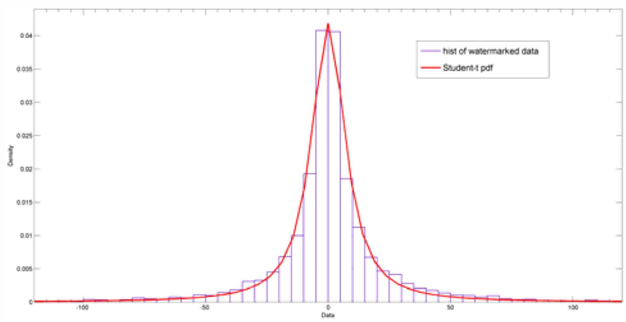

Figure 1. Watermarked data samples histogram of DCT domain of image ÒBaboonÓ and its Student-t pdf model fitting

An alternative known model the Cauchy member of SaS distributions and has been a valid approach for the watermarking problem as this proposed in work of [5]-[7]. In this work, we claim that DCT coefficients follow the Student-t distribution, since empirical distribution of these coefficients although they remain bell-shaped as the Gaussian model, they tend to have significant heavier tails [6], [18]. In Figure 1 we can see data histogram of DCT domain of image ÒBaboonÓ and its Student-t pdf model fitting.

B. *DWT domain*

As indicated in the work of Mallat on wavelets [20], detail subbands can be well described by GGD [7], [8]. In work of Kwitt [7], an alternative Cauchy model was also used for the same detail coefficients. In this work, we propose a two-scale decomposition, as in [10] and we model the second levelÕs detail coefficients with Student-t pdf. In Figure 2, we can see the data histogram of horizontal data details of image ÒBaboonÓ

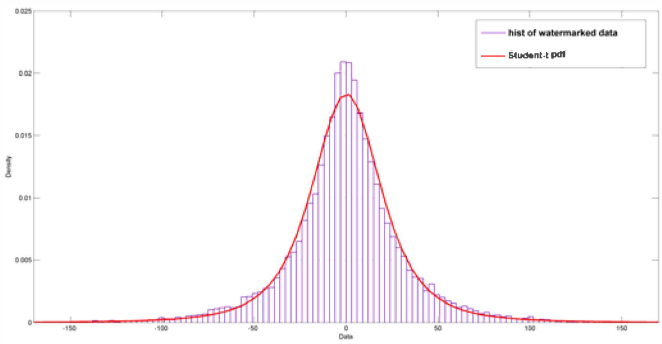

Figure 2. Watermarked data samples histogram of 2ndÕs level horizontal details of image ÒBaboonÓ and its Student-t pdf model fitting

In what follows we briefly review some of the most applicable distributions in additive watermarking for DCT and DWT domains.

C. *Generalized Gaussian Density*

The pdf of GGD is given by: $p(x) = Ae^{-|bx|^c}$ (7)

where $-\infty < x < +\infty$ and $b, c > 0$ [8], [20]. Generally GGD is a widely adopted model for DWT detail subband coefficients or DCT coefficients [4], [7]. Heavy-tailed behavior is a critical characteristic and towards parameters estimation we have to find the ML estimation [7]. Notice that shape parameter c is equal to two for the Gaussian distribution and one for the Laplacian pdf. Usually a fixed value of c offers almost the same detection performance without the estimation partÕs computational cost. Notice that, the smaller the shape parameter is, the more impulsive the shape and the heavier the tails [4].

D. *Cauchy distribution*

The pdf of Cauchy is given by: $p(x) = \dfrac{1}{\pi}\dfrac{\gamma}{\gamma^2 + x^2}$ (8)

with $-\infty < x < +\infty$. Cauchy also has heavy tails and with regard to distributionÕs parameters we resort to ML estimation as this depicted in work of [5]-[7].

E. *Detectors*

In this work, we have three test statistics of interest: two of them are derived after nonlinear processing based on Cauchy and Student-t distribution and the third one is the known GGD based detector:

1. *Generalized Gaussian:*

$$l(Y) = \sum_{i=1}^{N} b^c \left(|Y[i]|^c - |Y[i] - W[i]|^c \right) \quad (9)$$

2. *Cauchy with nonlinearity:*

$$l(Y) = \sum_{i=1}^{N} \frac{2Y[i]W[i]}{Y[i]^2 + \gamma^2} \quad (10)$$

3. *Student*-t with nonlinearity:

$$l(Y) = \sum_{i=1}^{N} \frac{(\nu+1)Y[i]W[i]}{\left(\frac{\nu}{\lambda} + Y[i]^2\right)} \quad (11)$$

V. Experimental Results

A number of experiments have been conducted to measure the sensitivity of the proposed detectors along with the ability to resist against attacks. Thus, the detection performance is measured by ROC (Receiver Operating Characteristic) curves. Our test images are the known ÒLenaÓ and ÒBaboonÓ images, whereas for statistical significance reasons we make use of Microsoft Object Recognition Image Database [17]. All the images have varying image content and their size is 512x512 pixels. Using DWT domain we applied the Daubechies-8 2D separable filters.

Using only one image we generate 100 1-bit spread-spectrum watermarks and at every execution we calculate the corresponding test statistic with and without the watermark. This happens for varying levels of watermarkÕs power quantification. In the case of the dataset, for every image we add the a common watermark and we evaluate the test statistic for the watermarked and the un-watermarked case.

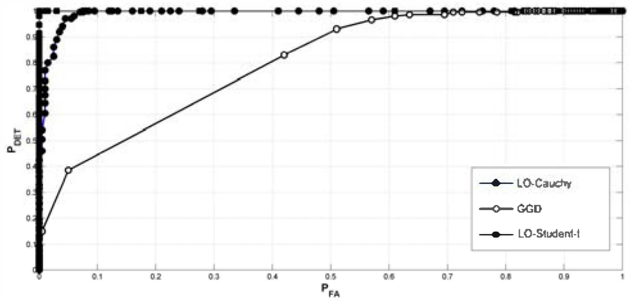

Figure 3. DWT-domain. ROC curves for detectorÕs comparison in a dataset of images (without attacks), WDR=-44 dB

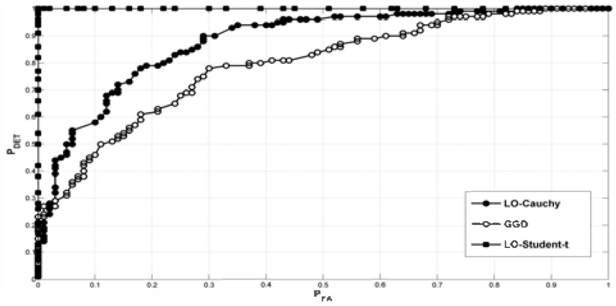

Figure 4. DWT-domain. ROC curves for detectorÕs comparison without attacks based on ÒLenaÓimage, WDR=-31.1 dB

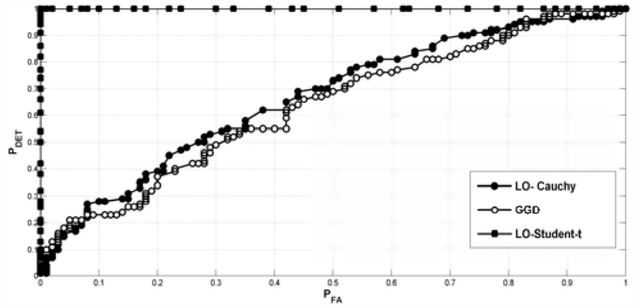

Figure 5. DWT-domain. ROC curves for detectorÕs comparison without attacks based on ÒBaboonÓimage, WDR=-37 dB

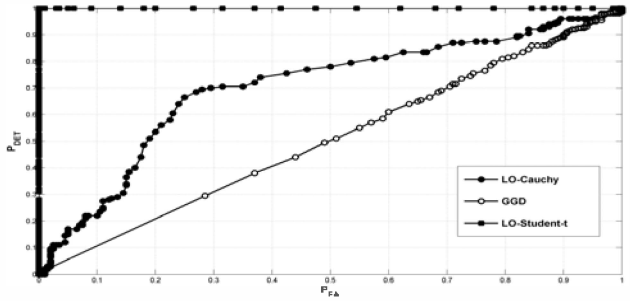

Figure 6. DWT-domain. ROC curves for detectorÕs comparison in a dataset of images (JPEG attack, qf=10), WDR=-29.9 dB

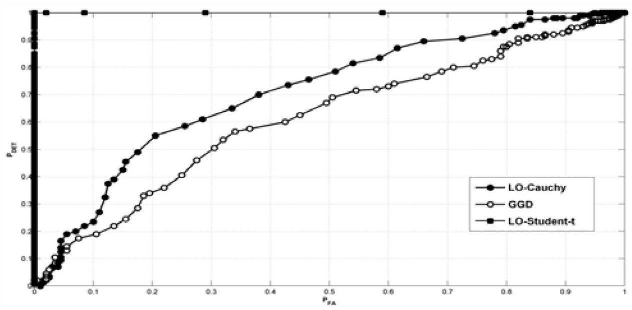

Figure 7. DWT-domain. ROC curves for detectorÕs comparison in a dataset of images (Wiener+AWGN attack), WDR=-29.9 dB

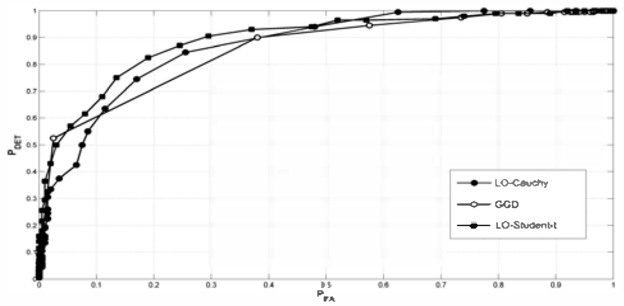

Figure 8. DCT-domain. ROC curves for detectorÕs comparison in a dataset of images (without attacks), WDR=-22.8 dB

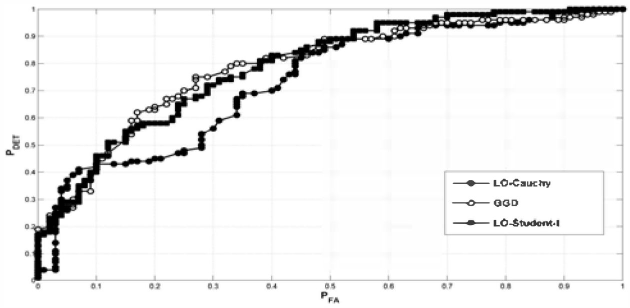

Figure 9. DCT-domain. ROC curves for detectorÕs comparison without attacks based on ÒLenaÓimage, WDR=-24.7dB

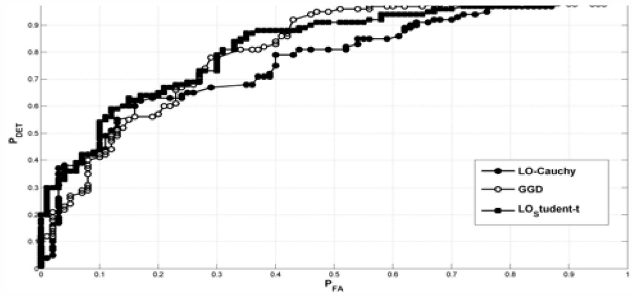

Figure 10. DCT-domain. ROC curves for detectorÕs comparison without attacks based on ÒBaboonÓ, WDR=-31.9 dB

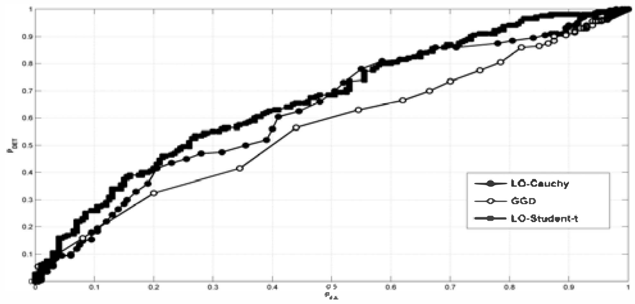

Figure 11. DCT-domain. ROC curves for detectorÕs comparison in a dataset of images (JPEG attack, qf=10), WDR=-22.8 dB

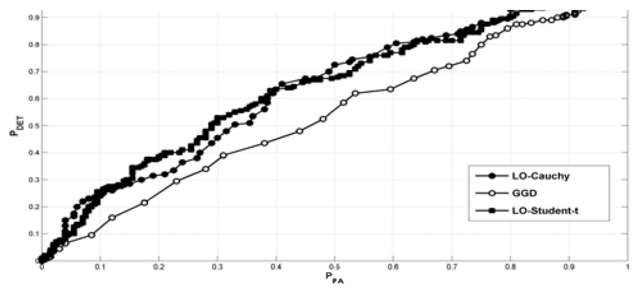

Figure 12. DCT-domain. ROC curves for detectorÕs comparison in a dataset of images (Wiener+AWGN attack), WDR=-22.8 dB

In order to provide comparable results we suggest the usage of Student-t detector after nonlinear preprocessing. To realize the scope of the comparison will use as a basis of comparison the known GGD model without preprocessing and the Cauchy model after nonlinear processing [6]. Thus, the detection sensitivity for all the detectors is evaluated on images without any kind of attack and images under compression attacks like JPEG and Wiener filter plus AWGN (Additive White Gaussian Noise) attack.

The validation of the detection performance is taking place for the same WDR (Watermark to Document Ratios) as defined in [6]:

$$WDR = 10\log\left(\frac{\sigma_w^2}{\sigma_x^2}\right) \quad \text{(dB)} \tag{12}$$

where σ_w^2, σ_x^2 are the watermark and original signal powers respectively defined as:

$$\sigma_W^2 = \frac{1}{N}\sum_{i=1}^{N} W[i]^2 \; , \; \sigma_X^2 = \frac{1}{N}\sum_{i=1}^{N} X[i]^2 \tag{13}$$

In Figure 3, we examine the performance of the aforementioned pdfs against the LO detector based on Student-t distribution. Using a dataset of images without any kind of attack for DWT-transformed images, we can observe that detection sensitivity of the proposed detection scheme is superior to the corresponding LO Cauchy-based and GGD detector. The same conclusion can be drawn for the case where we have Òrandom watermarksÓand a fixed image like ÒLenaÓ in Figure 4 and ÒBaboonÓin Figure 5. In Figures 6 and 7, we examine the robustness against JPEG attack and a signal processing attack like Wiener filtering plus AWGN attack. The curves show the same comparative relationship between the detectors by the performance criterion after some kind of attack. Thus the proposed t-based detectors under attacks still provide better detection results.

With regard to DCT domain, the proposed LO detectors were also applied. More specifically, we applied the statistical detectors in a corresponding plurality of coefficients as in the case of the DWT (10000 coefficients). Thus, putting transform coefficients in a zig-zag order we chose a diagonal band of low to medium frequencies in a full-frame DCT. The results show respective conclusions although not in the same extent.

From the work of [6] it is well known that the use of nonlinearities based on Cauchy pdf can lead to performance as good as or even better than that of the optimal GGD. In this study, we derive similar results, where the GGD detector uses the ML estimates for the model parameters. In addition, using Student-t detector, we have superior detection sensitivity against the corresponding LO-Cauchy detector and with the GGD based detector. This conclusion is understood in Figure 8, where t-based detectors in DCT domain are still more sensitive with regard to watermark detection. In Figures 9 and 10 we can observe the same results of the Òrandom watermarkÓ case for the two known images ÒLenaÓand ÒBaboonÓ

In the last two figures (11 and 12) we verify the robust properties of the proposed scheme in the DCT domain, since it has greater resistance to attacks. Thus in the case of the dataset of images, the effect of the attacks is similar for the two types under consideration for all the detectors and the proposed detector has slightly better performance than the other detectors.

VI. CONCLUSIONS

In this work, we studied the problem of locally optimum detection in the framework of additive watermarking. Working in a non-Gaussian environment, we developed a new test statistic based on Student-t modeling of transform coefficients (DWT and DCT). Extensive experiments on images with various statistical characteristics demonstrated the superiority of the proposed t-based locally optimum detector in comparison with known detectors based on alternative statistical models.

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