Image watermarking in the Hermite transform domain with resistance to geometric distortions

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ABSTRACT

This paper proposes a novel perceptual watermarking scheme operating in a Hermite transform domain. To achieve an acceptable level of watermark invisibility, masking properties of the Human Vision system (HVS) are exploited in the extraction of relevant local image features (texture, smooth regions, edges) for watermark embedding purpose. Many other works suggest the use of wavelets or contourlets. In our case, image features are extracted efficiently from the Hermite transform image representation which agrees with the Gaussian derivative model of the human visual perception. The resulting weighing mask is used to adapt the watermark strength to image regions during the embedding process.

In order to ensure watermark resistance to global affine geometric attacks (rotation, scaling, translation and shearing) the design of the watermarking scheme is modified, mainly, by incorporating a normalization procedure. Image normalization, a means to achieve invariance to geometric transformations, is well known in computer vision and pattern recognition areas. In this new design, both watermark embedding and detection are carried out in the Hermite transform domain of moment-based normalized images.

A sequence of tests is conducted on various images. Many removal attacks (JPEG compression, additive noise and filtering) as well as geometric attacks are applied from the Checkmark benchmark. Experimental results show the effectiveness of the whole scheme in achieving its goals in terms of watermark invisibility and robustness.

Keywords: Adaptive watermarking, Hermite transform, geometric attacks, image normalization.

1. INTRODUCTION

The protection of intellectual property has become a major issue because of the simplicity to modify and distribute digital content. This has generated the necessity that these contents can be identified by the owner through an efficient technique. Watermarking possess a viable solution to this problem.

Image watermarking consists of introducing a signal or data within the image data with the purpose of proving intellectual property, and authentication. The watermark may be inserted in the spatial domain or any other domain such as frequency [14]. In order to assess the performance of the technique used, one should look at the results it produces on two factors that have become standard measures in this area: invisibility or transparency, and robustness against attacks.

Within this context, the term "invisibility" means that, a priori and under normal conditions, the human eye can not perceive any change with respect to the original image. On the other hand, "robustness" means that watermark removal must be a complicated task, either through common operations (i.e. compression, filtering) or geometric manipulations (i.e. cropping, resampling, rotation).

Many algorithms and different tools for watermarking have been proposed in recent years and a large part of them have opted for models that take into account the characteristics of the human vision system (HVS) in order to achieve good results from the standpoint of invisibility and robustness. These models are called *perceptual models* and the watermark that exploits the perceptual information is known as *perceptual watermark* [14]. This technique takes advantage of the frequency sensitivity, luminance sensitivity and contrast masking.

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A large part of the watermarking algorithms that insert invisible marks work in a domain different from spatial domain, that is, they do not make modifications to the pixels of the original image. Basically, the process of embedding the watermark consists of decomposing the original image using a specific model of representation, add the watermark in the domain of the transform and reconstruct the image using the inverse transform [14]. Among the most widely used mathematical tools are discrete wavelet transform [3] (DWT), discrete cosine transform (DCT), discrete Fourier transform (DFT), fractal transform, Contourlet transform [2], among others.

The mathematical tool must be able to insert the watermark in the image so that a human observer can not detect it and it remains there even if modifications or transformations are applied on the image. From this, it is clear that the model should consider important characteristics of the human vision system (HVS). Young showed that Gaussians derivatives model receptive fields as well as retinal and cortical cell profiles more accurately than other functions such as Gabor [16,17]. Similar to receptive fields, Gaussians derivative functions are spatially local so that image features can be locally described in terms of these functions. In this paper we show that working with these functions allows embedding the watermark with the largest possible strength while remaining unperceivable by a human observer.

The Hermite [6] Transform (HT) is an image representation model that incorporates important properties of the human vision system: local orientation analysis and the Gaussians derivative model of early vision. Moreover, Gaussians derivatives functions have been long used in pattern recognition tasks and, in addition, they present certain type of symmetries related to scaling, rotation and translation, which are desirable when modeling and representing images primitives.

The HT is a special case of the polynomial transforms, when a Gaussian function is chosen as analysis window. The analysis functions are obtained by multiplying the Gaussian function by the Hermite polynomials [6]. In the same way as other transforms, the Hermite Transform also allows multi-resolution pyramids; this means that multiscale analysis is possible. Recently, the HT has been reformulated as a multiscale image representation model for local orientation analysis [12,5].

From a practical perspective the HT is also useful: its basis functions are orthogonal with respect to the Gaussian weighted window, which allows perfect image reconstruction [8]; and it is a separable, which allows efficient implementation.

Similarly to a wavelet decomposition, the HT decomposes the image into a number of coefficients. Zero order coefficients represent a Gaussian-weighted image average, whereas the higher-order coefficients contain image details. In order to obtain unperceivable watermarks, the information must be embedded into the higher-order coefficients and the zero-order coefficients must be kept intact.

HVS perception suggests that a pattern can be recognized even if it has been scaled or rotated (invariance to scaling and rotation). Therefore, if a watermark is embedded into the image, it is expected that the watermark could be maintained and/or detected after these operations. In practice, it does not happen. Any change, however small, can affect the geometric synchronization and cause misdetection of the watermark.

In order to minimize the effects of a geometric attack, the image must be normalized [1,4], i.e. the original image must be transformed into another one in which the orientation and scale of objects in the image are fixed. This process can be achieved by transformations invariant to distortions of the image. Invariant transformations are independent of the content of the image and its particular characteristics [15]. Methods that use this strategy take advantage of invariance properties in the domain of the transform in order to embed watermarks resistant to attacks. Among the possible options of image invariants are the moments, projective and algebraic invariants [9]. Moments provide the parameters needed for image normalization, i.e. the rotation angle and the scaling factor. Once the image has been normalized, the watermark is added through the proper marking scheme. After embedding, the image is rotated and scaled back to its original condition.

Section 2 is a description of the Hermite transform as an image representation model. In section 3, we present a perceptual watermarking algorithm operating in the Hermite transform domain. In section 4, we develop the watermark embedding and detection steps when image normalization is applied. Section 5 summarizes main experimental results and discus invisibility and robustness issues regarding the proposed watermarking schemes. Concluding remarks are drawn in section 6.

2. THE HERMITE TRANSFORM AS AN IMAGE REPRESENTATION MODEL

The Hermite transform [6,7] is a special case of polynomial transform. It can be regarded as an image description model. Firstly, windowing with a local function $\omega(x,y)$ takes place at several positions over the input image. Next, local information at every analysis window is expanded in terms of a family of orthogonal polynomials. The polynomials $G_{m,n-m}(x,y)$ used to approximate the windowed information are determined by the analysis window function and satisfy the orthogonal condition:

$$\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\omega^2(x,y)G_{m,n-m}(x,y)G_{l,k-l}(x,y)\,dxdy=\delta_{nk}\delta_{ml} \tag{1}$$

for $n,\ k=0,\ldots,\ \infty$; $m=0$; $n,l=0,\ldots,k$; where δ_{nk} denotes the Kronecker function.

Psychophysical insights suggest using a Gaussian window function, which resembles the receptive field profiles of human vision, i.e.

$$\omega(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right) \tag{2}$$

The Gaussian window is separable into Cartesian coordinates, it is isotropic, thus it is rotationally invariant and its derivatives are good models of some of the more important retinal and cortical cells of the human visual system [16,17].

In the case of a Gaussian window function, the associated orthogonal polynomials are the Hermite polynomials [13]:

$$G_{n-m,m}(x,y)=\frac{1}{\sqrt{2^n(n-m)!m!}}H_{n-m}\left(\frac{x}{\sigma}\right)H_m\left(\frac{y}{\sigma}\right) \tag{3}$$

where $H_n(x)$ denotes the *n*th Hermite polynomial

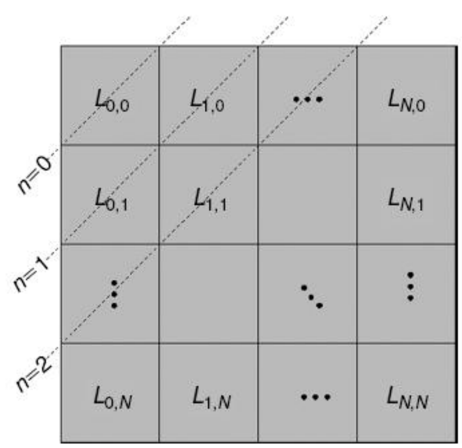
The original signal $L(x,y)$, where (x,y) are the pixel coordinates, is multiplied by the window function $\omega(x-p,y-q)$, at positions p,q that conform the sampling lattice S.

Through replication of the window function over the sampling lattice, a periodic weighting function is defined as $W(x,y)=\sum_{(p,q)\in S}\omega(x-p,y-q)$. This weighting function must be different from zero for all coordinates (x,y), then:

$$L(x,y)=\frac{1}{W(i,j)}\sum_{p,q\in S}L(x,y)\omega(x-p,y-q) \tag{4}$$

The signal content within every window function is described as a weighted sum of polynomials $G_{m,n-m}(x,y)$ of m degree in x and $n-m$ in y. In a discrete implementation, the Gaussian window function may be approximated by the binomial window function, and in this case, its orthogonal polynomials $G_{m,n-m}(x,y)$ are known as the Krawtchouck's polynomials.

The polynomial coefficients $L_{m,n-m}(p,q)$ are calculated by convolution of the original image $L(x,y)$ with the function filter $D_{m,n-m}(x,y)=G_{m,n-m}(-x,-y)\omega^2(-x,-y)$ followed by subsampling at positions (p,q) of the sampling lattice S, i.e.,


$L_{0,0}$
$L_{1,0}$
$L_{N,0}$
$L_{0,1}$
$L_{1,1}$
$L_{N,1}$
$L_{0,N}$
$L_{1,N}$
$L_{N,N}$
n=0
n=1
n=2

3. PERCEPTUAL WATERMARKING IN THE HERMITE TRANSFORM DOMAIN

Given the attractive properties of the Hermite transform, we developed a perceptual watermarking technique which expands on a well-known algorithm already implemented on wavelets and contourlet image transforms [2,3]. Adaptation to the Hermite transform domain is accompanied by few modifications. We have mainly exploited the transform redundancy and equal-sized subbands property to allow for more accurate processing and improved localization of captured Hermite features.

3.1 Watermark embedding

First, the original image of size *XxY* is decomposed into N^2 Hermite subbands, each of size *XxY*. Second, the watermark W to be embedded is arranged as a set of one or more matrices $W_{n.m}(i,j)$ with size *XxY* and pseudo-random binary values {-1,1}. A private key P is used as a seed to generate those pseudo-random values. The indices n, m indicate which Hermite subband coefficients $L_{n,m}$ are being marked with $W_{n,m}$. Inserting watermark data into the Hermite coefficients of the image is accomplished according to the following equation:

$$L'_{n,m}(i,j) = L_{n,m}(i,j) + \alpha \; M(i,j) \; W_{n,m}(i,j) \tag{7}$$

where $L'_{n,m}$ are the marked Hermite subbands, α is a strength control parameter, and M is a weighing mask used to adapt the level of watermark strength and invisibility according to the local characteristics of the image. The weighing mask, of size *XxY*, is calculated here by introducing some modifications to the approaches proposed in [2][3]. The eye sensitivity to noise and brightness variations, as well as the presence of significant image features (textures, edges) are taken into consideration. M is created as:

$$M(i,j) = \frac{1}{2} B(i,j) T(i,j)^{0.2} E(i,j)^{0.2} \tag{8}$$

where

$$B(i,j) = 1 + \tfrac{1}{256} L_{0,0}(i,j) \tag{9}$$

$$T(i,j) = Var\left\{ L_{0,0}(i+y, j+x) \right\}_{x=0,1;\, y=0,1} \tag{10}$$

$$E(i,j) = \frac{1}{4N^2} \sum_{n=1}^{N} \sum_{m=1}^{N} \sum_{x=0,1} \sum_{y=0,1} \left[L_{n,m}(i+y, j+x) \right]^2 \tag{11}$$

The factor B is proportional to brightness values of the coarse resolution sub-image $L_{0,0}$ whereas T and E capture respectively the neighborhood texture activity in the coarse subband and the presence of oriented image edges in detail subbands. Defining which coefficients are marked with which watermark is left to the experimental part. After the embedding stage, the watermarked image is built using the Hermite transform reconstruction algorithm.

3.2 Watermark detection

The watermark detection algorithm is based on comparing a correlation value R' to a given threshold T. The value R' is an average measure of the correlation between the watermark data and the appropriate Hermite coefficients of a given image. Assuming a watermark W, a given image, and a marking scheme with K as the total number of marked Hermite subbands, the detection procedure begins with the decomposition of the given image into its Hermite coefficients and then computes the correlation R' according to the following equations:

$$R' = \frac{1}{K} \sum_{n} \sum_{m} R(n,m) \tag{12}$$

where

$$R(n,m) = \begin{cases} \dfrac{1}{XY} \displaystyle\sum_{i=1}^{X} \sum_{j=1}^{Y} L'_{n,m}(i,j) \; W_{n,m}(i,j) & if \;\; L'_{n,m} \;\; is \;\; marked \\ 0 \quad otherwise. \end{cases} \tag{13}$$

If $R'>T$ then the watermark W is present in the image. This watermarking method is blind since the detection process does not require the use of the original unmarked image. To determine the value of the threshold T, we adopted the *a posteriori* computation [3] to the marked Hermite coefficients as follows:

$$T = 3.97\sqrt{2\sigma^2} \tag{14}$$

where

$$\sigma^2 = \frac{1}{(KXY)^2}\sum_n \sum_m \sum_{i=1}^{X} \sum_{j=1}^{Y} L'_{n,m}(i,j)^2 \tag{15}$$

4. WATERMARKING ROBUST AGAINST GEOMETRIC DISTORTIONS

In the previous section, we designed an efficient blind watermarking scheme which achieves watermark invisibility and strong robustness against several removal attacks (jpeg compression, additive noise, filtering…), as shown in the experimental result section. Unfortunately, embedded watermarks by means of perceptual algorithms, such as the one described above, are vulnerable to geometric attacks. Indeed, watermark detection is easily disabled due to the watermark desynchronization that occurs when watermarked images undergo geometric attacks (rotation, scaling, translation ...). Therefore, the proposed approach consists in performing both watermark embedding and detection in a geometric invariant image subspace. Moment-based image normalization is among the commonly suggested approaches to handle geometric attacks in blind watermarking methods [1,4,9,15].

4.1 Moment-based image normalization

We consider global affine geometric transforms such as rotation, scaling, translation, shearing or any combination of these four elementary transforms. In this context, a normalization procedure is aimed to transform an image and each of its affine transforms into a unique standard form, called the normalized image, and which meets a given set of image moment values. Therefore, normalization is a way to compensate for any affine geometric distortion and ensure invariance property to the normalized image.

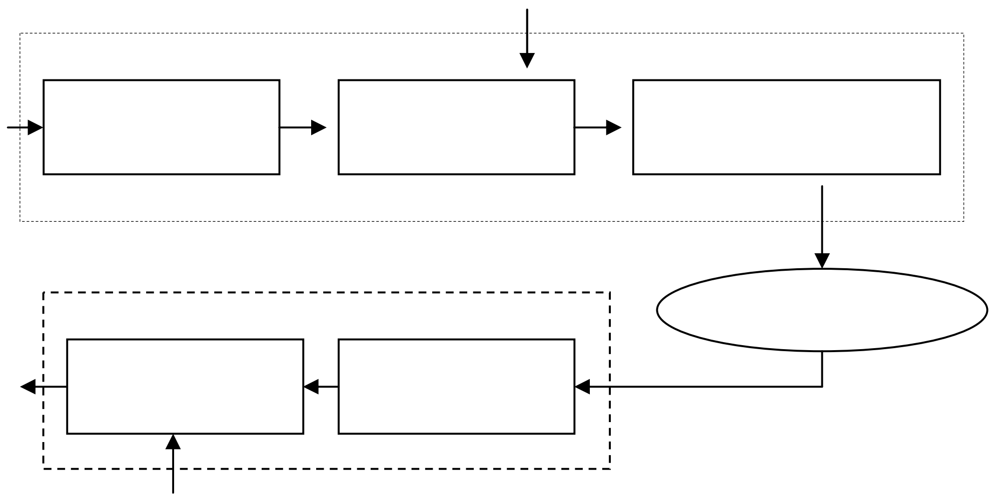
The proposed normalization procedure in [4] is based on the fact that any general affine geometric distortion can be expressed as a composition of translation, shearing (in both x and y) direction and scaling. Therefore, the normalizing steps for a given image consist on applying a sequence of 4 elementary transformations (i.e. translation, x and y shearing and scaling) to compensate for the aforementioned distortions. At each step, predefined moment criteria are exploited to calculate the transform parameters. For example, the scaling factor is calculated in a way to achieve a predefined image size and null values for fifth order central moments. More computation details are provided in [4].

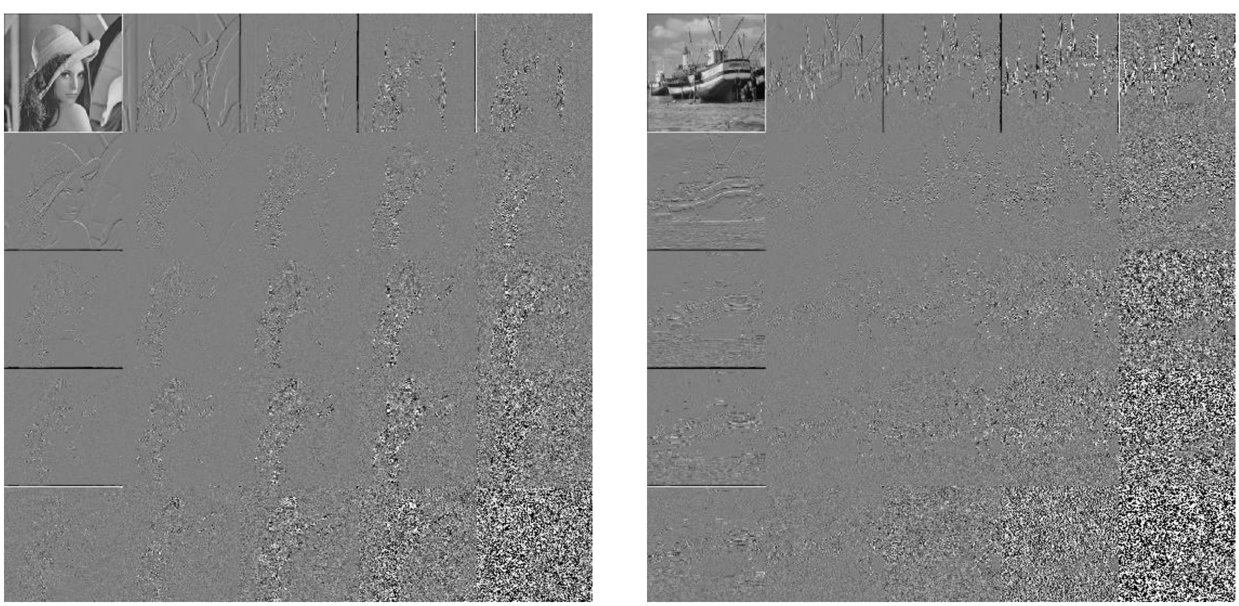
4.2 Watermarking in the normalized space

In this case, the watermark embedding and detection are carried out with respect to a normalized image which is intended to be in an invariant space against affine transform attacks. The functional diagram in Fig. 2. illustrates how normalization is incorporated in the whole watermarking scheme.

The embedding procedure is performed according to the following 10 steps:

1. Normalize the original image.
2. Apply the Hermite transform to the normalized image in 1 to produce NxN Hermite subbands.
3. Calculate the weighing mask M using the Hermite subbands in 2.
4. We assume that K predefined Hermite subbands $L_{n,m}(i,j)$ are being watermarked. Generate a watermark $W_{n,m}(i,j)$ for each subband in 2. If $L_{n,m}(i,j)$ is being watermarked then $W_{n,m}(i,j)$ is a matrix of pseudo-random binary values {-1,1}, otherwise $W_{n,m}(i,j)$ is a matrix of nul values. A private key P is used as a seed to generate those pseudo-random values. Note that $W_{n,m}(i,j)$ is of the same size as the subband $L_{n,m}(i,j)$.
5. Multiply each watermark $W_{n,m}(i,j)$, obtained in step 4, by the weighing mask M to produce a sort of a virtual map of Hermite coefficients.
6. Apply the inverse Hermite transform to the coefficient map created in 5 to produce W'.
7. Create a binary mask with the support area of the normalized image in 1. This mask has values equal to 1 in the support area and 0 elsewhere.
8. Multiply W' by the mask calculated in step 7 to mask off the boundary area.





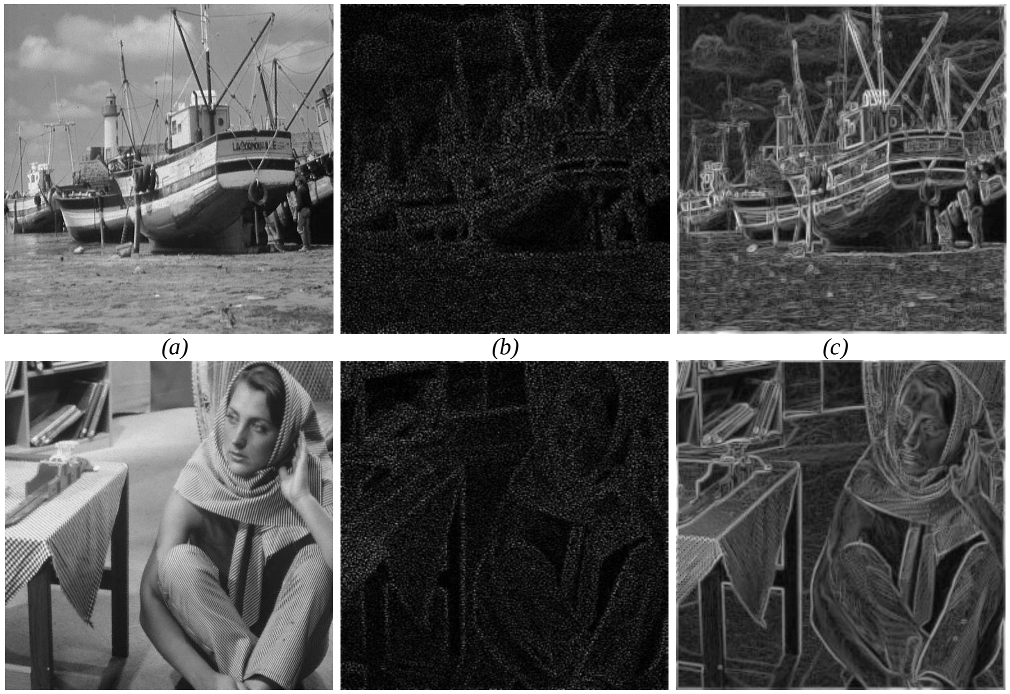


Fig. 4. *(a)*The watermarked Boat and Barbara images, *(b)* absolute difference with the original image, magnified by a factor 8, and *(c)* the Hermite-based weighing mask *M*.

5. EXPERIMENTAL RESULTS

To assess the efficiency of the proposed watermarking schemes, various tests were applied on various images and the standard benchmark Checkmark [10] was adopted. The experiments presented here were performed on the well known images; Lena, Boat, Baboon and Barbara. The size of each one was 512x512.

The focus of a first experimental part was mainly on validating the perceptual watermarking technique in the Hermite transform domain. In a second experimental part, the potential of the incorporated moment-based normalization was examined and evaluated in terms of added robustness against global affine geometric attacks.

5.1 Hermite-based perceptual watermarking

First, the original image was decomposed into its Hermite coefficients using the parameter values $\sigma = \sqrt{2}$ (for the Gaussian window spread) and subsampling factor of one (for the sampling lattice). As shown in Fig.1 and Fig. 3., the resulting Hermite coefficients were arranged as a set of 25 equal-sized subbands; a coarse subband $L_{0,0}$ representing a Gaussian-weighted image average and 24 detail subbands $L_{,n,m}$ corresponding to higher-order Hermite coefficients. Second, the perceptual watermarking scheme, described in Sec. 3, was applied. The perceived quality of watermarked images and PSNR values between original and watermarked images were examined to appreciate the degree of watermark invisibility as well as the power of Hermite weighing mask in enhancing the localization of relevant embedding regions.

Many parameters were adjusted so as to meet a reasonable tradeoff between correct watermark detection and perceived invisibility. Therefore, adopting watermark embedding on second-order Hermite coefficients $L_{0,2}$, $L_{1,1}$ and $L_{2,0}$ provided great satisfaction as shown in Fig. 4 and Table 1.

In order to evaluate the robustness of our watermarking scheme, jpeg compression, additive noise and many other Checkmark attacks were applied to watermarked images. A sample of the corresponding watermark detection results (i.e. correlation values *R'*, threshold values *T* and the number of correct detections) are presented in Fig.5, Fig.6 and Table 2.

In Fig. 5, a watermarked Lena image was jpeg compressed with respect to many quality factors from 1 to 100. For each compressed image, we collected its detection response over 1000 different watermarks including the right one (i.e. the embedded watermark). For quality factors higher then 5%, the detection response *R'* to the right watermark was always

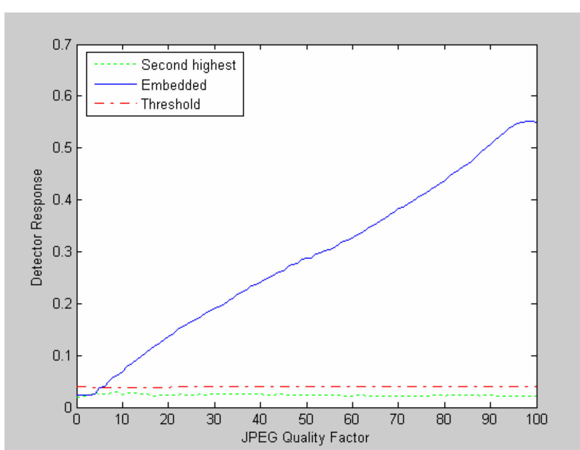

Second highest
Embedded
Threshold
Detector Response
JPEG Quality Factor
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
10
20
30
40
50
60
70
80
90
100

Fig. 5. Detector response to increasing JPEG quality factors on a watermarked Lena image. 1000 marks were tested , among them, the embedded one.

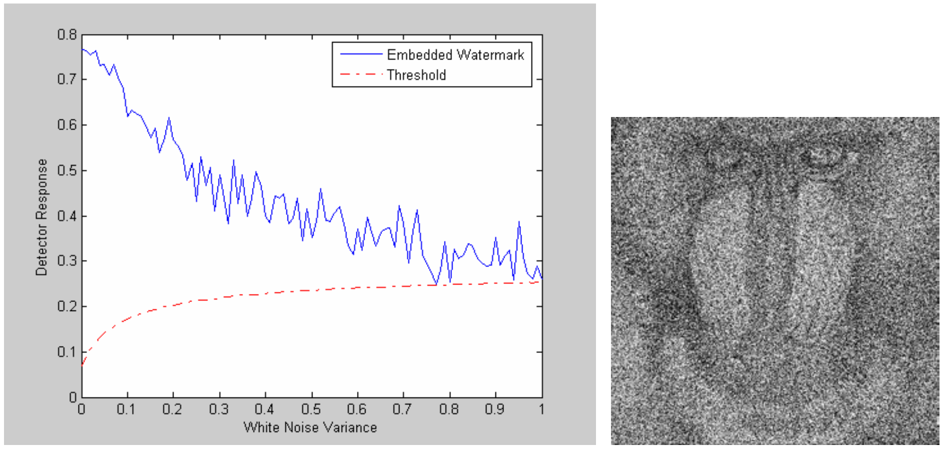


Fig. 6. (Left) Detector response to increasing additove white noise variance on Baboon image. (Right) A watermarked Babbon image with additive noise (noise variance = 0.35).

Table 2. Examples of Checkmark attacks on a watermarked Lena image.

Type and number of Attacks	Average number of correct watermark detection
Remodulation(4)	100%
Filtering(3)	100%
Cropping(28)	100%
Sharpening(1)	100%
Shearing(14)	0%
Scale(42)	0%
RotationScale(21)	0%
Rotation(21)	0%

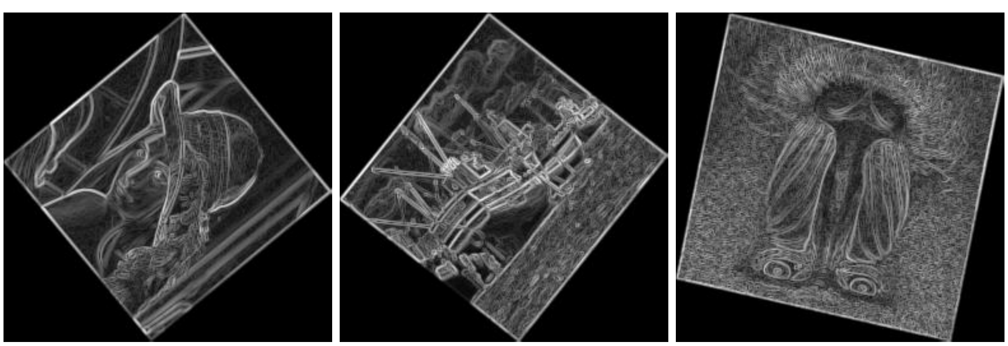


Fig. 7. Construction of Hermite-based weighing masks in the normalized space.