

Optimizing Perceptual Shaping of a Digital Watermark Using Genetic Programming

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Abstract—Embedding of a digital watermark in an electronic document is proving to be a feasible solution for copyright protection and authentication purposes. In this paper, we present an innovative scheme of perceptually shaping watermark to the cover images. A watermark is generally embedded in the selected coefficients of the transformed image using a carefully chosen watermarking strength. Choice of a good watermarking strength, to perceptually shape the watermark according to the cover image is crucial to make a tradeoff between the two conflicting properties, namely: robustness and imperceptibility of the watermark. Traditionally, a constant watermarking strength obtained from spatial activity masking and heuristics has been used for all the selected coefficients during embedding. We consider this tradeoff as an optimization problem and have investigated an evolutionary optimization technique to find optimal/near-optimal perceptual shaping function for DCT based watermarking system. The new scheme provides an excellent tradeoff between the robustness and imperceptibility and is image adaptive. Improved resistance to attacks, especially against JPEG compression of quality 7% and Gaussian noise of variance 17000 has been observed.

Index Terms—Digital watermarking, perceptual shaping, genetic programming, watermarking strength, human visual system, spatial activity.

I. INTRODUCTION

A DIGITAL watermark can be described as a visible or preferably invisible identification code that is permanently embedded in the data [1]. It means that unlike conventional cryptographic techniques, it remains present within the data even after the decryption process. In invisible watermarking, the embedding must be done in such a way that the embedded signal is hidden and thus does not seriously affects the marked image quality. But at the same time, it should resist common degradations that the host signal does. The former property is called imperceptibility, while the later one is called robustness of a watermarking system. Digital watermarking is thus suitable for several applications like copyright marking, broadcast monitoring, data authentication and covert communications etc.

In digital watermarking, using the overall information about the image characteristics, the watermark is generally embedded in the whole image with the same strength without considering the local distribution of the cover

image content. This embedding usually leads to unwanted visible objects, especially in regions, which are more sensitive to noise (smooth regions). In order to decrease these deformations, the watermarking strength should be decreased. However in doing so, robustness is lost. Therefore one needs to perceptually shape the watermark, providing a suitable watermarking strength for each of the selected discrete cosine transformation (DCT) coefficients.

Generally, watermarking in frequency domain has been used [2]-[4], as it allows the direct understanding of the contents of the image. Consequently, the characteristics of human visual system (HVS) can be taken into account more easily when one needs to decide the strength and position of the watermark to be added to the image. Boland *et al.*, [5] have employed frequency domain transformation on block by block basis, while Barni *et al.* [1] and Cox *et al.* [2], have employed transformation to the image as a whole. Recently, Miller *et al.* [6] and Hernandez *et al.* [7] have used Watson's perceptual model [8] to perceptually shape the watermark according to the cover image before embedding. But their watermarking scheme is based on 8×8 block-based DCT domain watermarking. On the other hand, rather than optimizing perceptual shaping, Huang *et al.*, [9], [10] use Genetic Algorithms to find the optimal embedding positions in a block-based DCT domain watermarking schemes to improve marked image quality. In the present work, we are concentrating on the optimization of perceptual shaping of a watermark in the whole DCT domain watermarking system as used in [3].

The term genetic programming (GP) was introduced independently by Koza and Garis in 1990 [11]. Since then it has received widespread applications in research academia. It is a type of evolutionary algorithms that are inspired by the mechanism of natural selection. They have been shown to perform well when the space to be searched is very large. GP operates iteratively on a population of structures (normally trees), each of which represents a candidate solution to the problem. In our scheme, a tree represents perceptual shaping function (PSF) that is tested for embedding.

Using functions and terminals for tree generation, a randomly generated set of such trees representing an initial population is formed. Then GP starts its search for the optimal/near-optimal solution in the search space using this initial population. Three basic genetic operators guide this search: selection, crossover and mutation. Selection is the process of selecting the best individuals for mating to produce next generation. The quality criteria, with which one determines an individual that should be selected for mating is called fitness [11]. Crossover and mutation are two variation operators used to produce offspring of the best individuals. Mutation changes a small part of an

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individual. However, crossover changes genetic material usually between two materials to create an offspring that is a combination of its parents. In this work we have used GP to automatically produce an optimal/near-optimal PSF that embeds a watermark of high overall energy content at lower cost to visibility.

DCT domain watermarking techniques are important due to the extensive use of the DCT in many image and video compression standards. The DCT based watermarking techniques provide good resistance against many attacks, except geometrical attacks like rotation. In this work we have improved its resistance by embedding a watermark of high overall strength and still keep high invisibility of the watermark.

The paper is organized as follows. In Section II, we briefly describe the theory of watermarking, including watermark casting and watermark detection. Next in Section III, our proposed technique of optimizing PSF is discussed. In Section IV, the implementation details of evolving PSF using GP are discussed. Results and discussion are presented in Section V. Finally, we finish with conclusions in Section VI.

II. WATERMARKING THEORY

Digital watermarking is a process of embedding information (or signature) directly into a multi media data by making small modifications. These small modifications however should not affect the visibility of the image to a large extent. Similarly these small modifications should be able to survive intentional and unintentional attacks (i.e. should have robustness). Robustness is difficult to achieve, since both security levels and operational requirements are usually application dependent. In this work we are focusing on image watermarking which means that image should be able to survive common image preprocessing techniques and forgery attacks. In order to achieve invisibility, Cox *et al.*, [2] proposed to use a pseudo-random sequence of real numbers as the watermark. These sequences should be numerous and easily retrievable. Following his idea we are using a pseudo-random sequence of real numbers as the watermark. This whole process can be viewed as a communication task with the watermark acting like a signal and the cover image acting just like a channel. The intentional attacks and unintentional image processing can thus be considered just like the noise, which the signal should be immune to. Lastly the scheme should have the ability to detect or extract the signal from the corrupted image.

Based on the need of original cover image during the detection stage, there are mainly two types of watermarking techniques [12]: one, which requires the original image [2], and the other which does not [3]. We have followed the later approach, which is also called a blind detection scheme. In the following we explain the various steps taken in a typical watermarking system.

A. Digital Watermark Embedding and Detection Processes

Let $\mathbf{I}$ denote an original image of size $M \times N$ then its DCT transformed image $\mathbf{S}$ is given by:

$$S(u, v) = \frac{2}{\sqrt{MN}} a(u) a(v) \times \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m, n) \cos\left[\frac{(2m+1)u\pi}{2M}\right] \cos\left[\frac{(2n+1)v\pi}{2N}\right] \quad (1)$$

where

$$a(u) = \begin{cases} \sqrt{1/M} & \text{for } u = 0 \\ \sqrt{2/M} & \text{for } u = 1, 2, \dots, M-1 \end{cases}$$

and

$$a(v) = \begin{cases} \sqrt{1/N} & \text{for } v = 0 \\ \sqrt{2/N} & \text{for } v = 1, 2, \dots, N-1 \end{cases}$$

In order to select coefficients for embedding, a zigzag scanning of the transformed image in DCT domain is done [3]. It is equivalent to sorting according to importance, since the perturbation in the low frequency components is generally more perceivable to human eyes than high frequency components. The first L coefficients are left intact and the watermark is added to the next G coefficients. Suppose the first $L+G$ DCT coefficients are:

$$\mathbf{T} = [t_1, t_2, \dots, t_L, t_{L+1}, \dots, t_{L+G}] \quad (2)$$

and the pseudo-random watermark is given by:

$$\mathbf{X} = [x_1, x_2, \dots, x_G] \quad (3)$$

The new coefficients after embedding are:

$$\hat{t}_{L+i} = t_{L+i} + \alpha |t_{L+i}| x_i \quad (4)$$

where α is the watermarking strength and i runs from 1 to G . These new coefficients are re-inserted into the zigzag scan. Watermark embedded image in spatial domain is then obtained by taking the inverse of modified DCT coefficients.

In the detection process, Piva *et al.* [3] used the reverse process for a given corrupted image. First the $M \times N$ DCT coefficients matrix is computed. It is then re-ordered by the zigzag scan. The $L+1$ to $L+G$ coefficients are selected to form a vector $\hat{\mathbf{T}}$ as follows:

$$\hat{\mathbf{T}} = [\hat{t}_{L+1}, \dots, \hat{t}_{L+G}] \quad (5)$$

The correlation Z of $\hat{\mathbf{T}}$ and any mark $\mathbf{Y}$ is calculated as:

$$Z = \frac{1}{G} \mathbf{Y} \cdot \hat{\mathbf{T}} = \frac{1}{G} \sum_{i=1}^G y_i \cdot \hat{t}_{L+i} \quad (6)$$

By comparing the correlation Z to a pre-defined threshold, they determine whether watermark exists or not.

B. Perceptual Shaping of a Watermark

In order to perceptually shape a watermark according to the cover image, such that a human observer could not easily notice it, one has to exploit the sensitivity/insensitivity of HVS. But HVS is a complex system that is mainly composed of three parts: a receiver with a pre-processing stage (the eye and the retina), a transmission channel (the optic nerve), and a processing channel (the visual cortex). Efforts to understand and model HVS have partly remained fruitless due to the lack of our knowledge about the way that a stimulus is processed through the huge neural network of our brain. Different techniques have

been used to exploit its properties and thus hide (mask) a signal into another signal. For example, edges in images can mask signals of much greater amplitude than regions having nearly constant intensity [13]. This fact is exploited by spatial masking. But spatial masking is relatively limited and is concentrated in a location only few pixels close to the edge. This makes it difficult for use in watermarking schemes. However, it is observed that regions in an image that are not smooth and have sharply changing luminance are able to mask other signals significantly. This phenomenon is called noise masking and is difficult to be modeled [14].

The concept of entropy masking has also been used, which states that masking is a function of the degree to which knowledge about a mask is uncertain [14]. The noisier a region is, the greater the entropy is. Nadenau *et al.* [15] gave the concept of similarity masking, which states that HVS is more sensitive to a distortion that does not look like its surroundings. Another technique, which is based on the subjective visual quality measurement, is called spatial activity [16]. The use of spatial activity relies on the fact that noise visibility decreases in areas with sharp luminosity variations, thus offering easy embedding of noise in these areas. Spatial activity $A_{m,n}$ around a pixel position (m,n) is defined as the sum of local variations of surrounding pixels.

Piva *et al.* [3] made use of the spatial activity to exploit the distinctiveness of the HVS to embed a watermark of high energy content in an image at low cost of visibility. In his method the original image $\mathbf{I}$ and the watermarked image $\hat{\mathbf{I}}$ are added pixel by pixel according to the local weighting factor $\beta_{m,n}$ thus obtaining new watermark image $\mathbf{I}$

$$i''_{m,n} = i_{m,n}(1 - \beta_{m,n}) + \beta_{m,n}\hat{i}_{m,n} = i_{m,n} + \beta_{m,n}(\hat{i}_{m,n} - i_{m,n}). \quad (7)$$

The weighting factor $\beta_{m,n}$ was used to take into account the characteristics of HVS. In highly textured regions, where noise sensitivity is low i.e. $\beta_{m,n} \approx 1$ and $i''_{m,n} \approx \hat{i}_{m,n}$. Whereas in uniform regions, where noise sensitivity is high $\beta_{m,n} \approx 0$ and $i''_{m,n} \approx i_{m,n}$. For each pixel intestines, $\beta_{m,n}$ was computed by obtaining variance of 9×9 non-overlapping blocks of the image. The average watermarking strength $\bar{\alpha}$ was thus obtained using $\beta_{m,n}$.

III. PROPOSED TECHNIQUE FOR OPTIMIZING PERCEPTUAL SHAPING OF WATERMARK

In this work GP is used to insure invisibility of watermark by optimizing perceptual shaping according to HVS. That human visual system is sensitive to local changes in variance of an image. A human observer can easily observe noise in smooth regions, but not in highly textured regions [17]. These local changes in variance can be traced by using spatial activity masking [16]. Spatial activity masking thus helps us to select those areas whose visibility will be less affected with watermark embedding. Then GP is used to evolve such a perceptual shaping function that embeds high strength watermark in high variance areas and low strength watermark in low variance areas. For this purpose, change in local variance of the marked image with respect to the original cover image is used as the fitness function in GP simulation.

It is difficult to simultaneously optimize robustness and perceptual invisibility. Therefore, we keep the mean squared strength (MSS) that represents a measure of robustness, in a suitable range and try to evolve such PSF that ensures maximum invisibility of the watermark $\mathbf{X}$. This PSF is allowed to have values in range of $[0, 1]$, as the alteration to a DCT coefficient should be a fraction of its value. However, it is constrained to have MSS greater than certain application dependent lower bound.

$$MSS = \frac{1}{G} \sum_{i=1}^G \alpha_i^2 \quad (8)$$

Since the evolved watermarking strength is no more a constant rather a distribution, therefore we can configure an interesting modification to the conventional watermarking scheme [3]. Conventionally, the marked image $\hat{\mathbf{I}}$ is given by:

$$\hat{\mathbf{I}} = \mathbf{I} + f(\mathbf{I}, \mathbf{X}) \quad (9)$$

The function $f(\mathbf{I}, \mathbf{X})$ dictates the embedding process and depends only on the original image and the pseudo-random mark. Generally it is given by:

$$f(\mathbf{I}, \mathbf{X}) = \mathbf{I} \cdot \mathbf{X} \quad (10)$$

A certain constant strength of this is added to the original image. Now, since we are not using constant watermarking strength for the image; rather we use PSF (denoted by α). Consequently in our case this function also depends on the PSF and the marked image $\hat{\mathbf{I}}$ is given by:

$$\hat{\mathbf{I}} = \mathbf{I} + f(\mathbf{I}, \mathbf{X}, \alpha) \quad (11)$$

with

$$f(\mathbf{I}, \mathbf{X}, \alpha) = \mathbf{I} \cdot \mathbf{X} \cdot \alpha \quad (12)$$

To shape the watermark according to the cover image, the PSF should depend on the value of the DCT coefficient to be altered. But a question arises here, that using the same PSF for the marked image, how one should expect the same perceptual shaping to be obtained at the detection stage. Here we assume that the DCT coefficients during the embedding process are not heavily altered due to constraint on the image fidelity [7]. The experimental results shown in Section V validate this assumption.

If α_i denotes the watermarking strength for a particular coefficient of the selected coefficients, then for our proposed scheme, (4) and (6) which are used for embedding and detection respectively are modified as:

$$\hat{t}_{L+i} = t_{L+i} + \alpha_i |t_{L+i}| x_i \quad (13)$$

$$Z = \frac{1}{G} \sum_{i=1}^G y_i \cdot t_{L+i}^* \cdot \alpha_i \quad (14)$$

IV. IMPLEMENTATION

To represent a possible solution with a GP tree, one needs to define suitable functions, terminals and fitness criteria according to the optimization problem [18]. We have used a variant of Kuhlmann *et al.* GP C++ code [19] for evolving PSF. Matlab® [20] has been used for the manipulation of the images including taking DCT of the

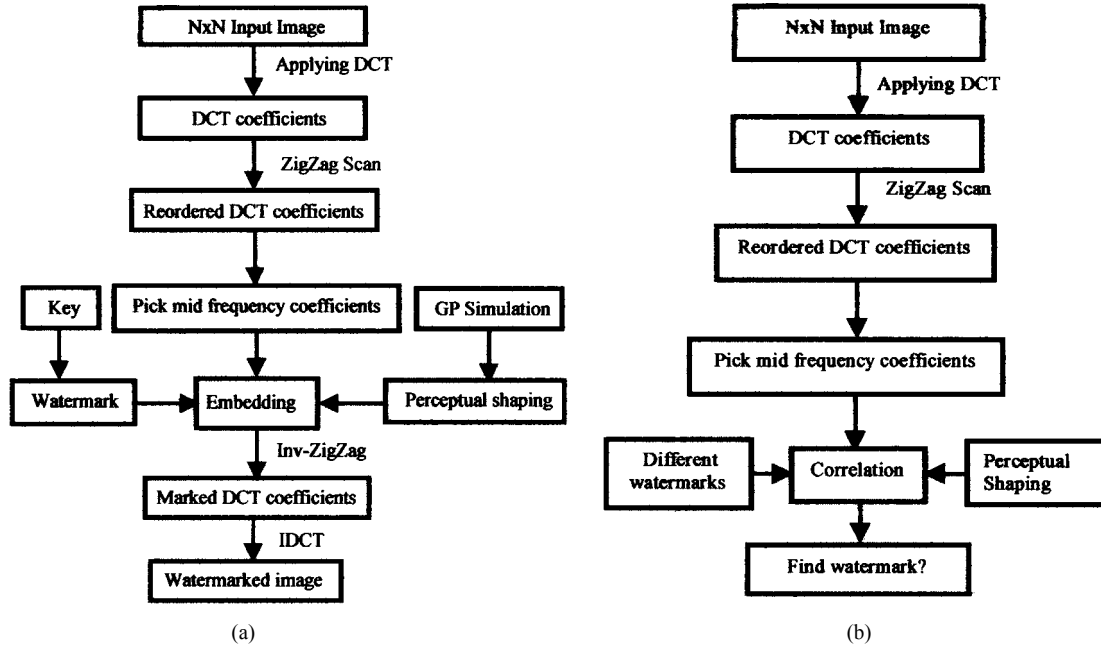


Fig. 1. (a) Watermark embedding, and (b) watermark detection.

TABLE I
GENETIC PROGRAMMING PARAMETERS

Objective	To evolve an optimal/near-optimal perceptual shaping function (PSF)
Function Set	+, -, *, protected division, IFGT, IFLT, EXP, and ABS
Terminal Set	Current DCT coefficient of SCA, index of SCA,
Fitness	$\frac{64}{M \times N} \sum_m \sum_n (BVM - BVM_0)$
Selection	Generational
Population Size	300
Initial Tree Depth Limit	6
Initial Population	Ramped half and half
Reproduction Prob.	20%
Mate Selection Prob.	80%
Operators	90% crossover and 10% mutation
Termination	Generation 30

cover image and the subsequent selection of the DCT coefficients. The selected coefficient array (*SCA*) is passed on to the GP C++ environment, where each PSF of the population is used for embedding in the *SCA*. The modified *SCA* is then sent back to the Matlab® environment and its fitness is computed based on its perceptual invisibility. This fitness of the individual PSF is again sent to GP C++ environment, where it dictates the mating probability for the creation of next generation. Typically, for a population size of 300 and 30 generations, the GP simulation takes about 46 hours on a Pentium IV–2.0 GHz machine.

The best PSF of the last generation is copied and is used for watermark embedding in Matlab® environment see Fig. 1. Its perceptual invisibility is checked using mean squared error (*MSE*) and signal to noise ratio (*SNR*) given by (15) and (16). Interfacing of Matlab® to VC++ has been used to coordinate among the different steps of the simulation. We have used Intel Pentium IV machine



Fig. 2. Marked Lena image.

with a processing speed of 2.0 GHz for our simulation studies.

$$MSE = \frac{1}{M \times N} \sum_m \sum_n [I(m,n) - \hat{I}(m,n)]^2 \quad (15)$$

$$SNR = 10 \log_{10} \left(\frac{\sum_m \sum_n [I(m,n)]^2}{\sum_m \sum_n [I(m,n) - \hat{I}(m,n)]^2} \right) \quad (16)$$

A. GP Configuration

Four binary floating arithmetic operators (+, -, *, *protected division*), if less than (IFLT), if greater than (IFGT), EXP and ABS are used as conventional functions in the GP tree. Nearly 200 constants between -1 and +1 are used as constant terminals (see Table I). Since for every DCT coefficient of *SCA*, GP has to decide the watermarking strength, therefore the current DCT coefficient value and its index *i* in *SCA* are set as the variable terminals in a GP tree.

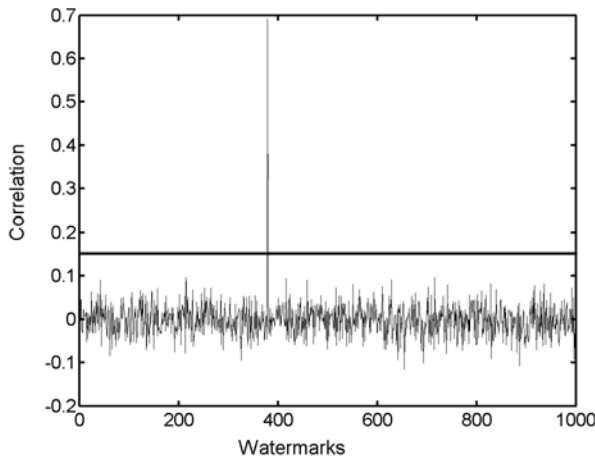


Fig. 3. Watermark detection.

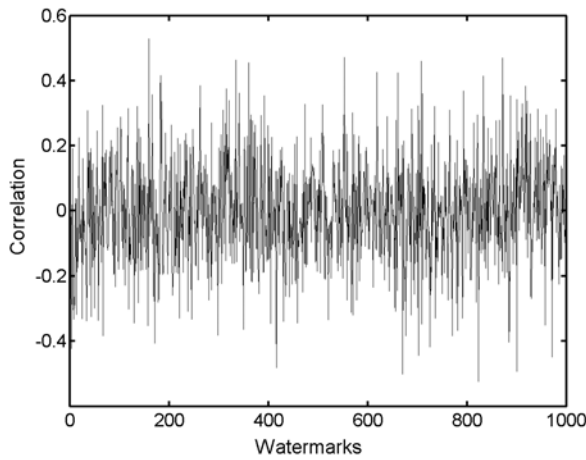


Fig. 4. Watermark detection without using PSF.

B. GP Fitness Criteria

Fitness of each PSF individual is computed based on perceptual invisibility using spatial activity masking. For this purpose first we obtain the marked image in spatial domain using inverse DCT of modified image. We then compute the variance of 8×8 non-overlapping blocks of the image. These blocks are replaced by their respective variances, which gives us a Block Variance Matrix (BVM) of size $M \times N/8 \times 8$. Difference between this BVM and that of the original image (BVM_0) is obtained. The mean of this difference is then used as the fitness of each PSF. The lesser the value of mean is, the higher is the perceptual invisibility and better the individual PSF has performed.

V. RESULTS AND DISCUSSION

A. Embedding and Detection:

In order to check the robustness of our proposed watermarking technique, we first use standard Lena image as a cover image. The marked image is shown in Fig. 2. The image is marked using $L = 25000$ and $M = 16000$, while block size for evaluating spatial activity masking is kept equal to 8×8 . About 1000 randomly generated watermarks are checked for correlation with the marked image. The response to the correct watermark ($seed = 379$) is much larger than the responses to the others (see Fig. 3). The correlation value is compared to a

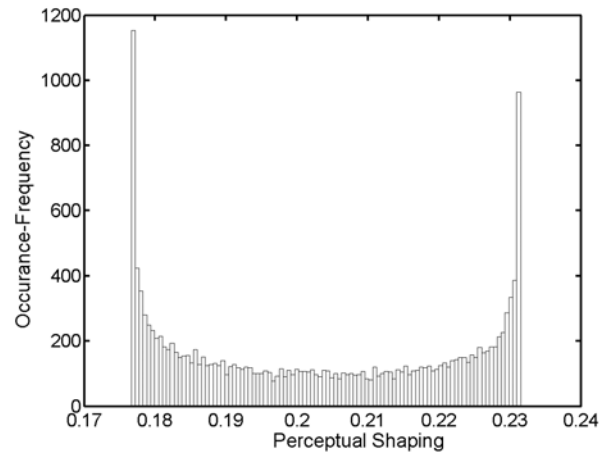


Fig. 5. Evolved perceptual shaping function (PSF).

TABLE II
PERFORMANCE OF EVOLVED PSF FOR DIFFERENT IMAGES

Standard Image	Mean Squared Strength (MSS)	SNR	MSE	Max. Gauss. Noise	Max. JPEG Comp.
Lena	0.0417	44.45	0.6287	7,000	6%
Mandrill	0.0417	36.28	3.884	30,000	4%
Jaguar	0.0418	38.24	2.847	25,000	6%
Boat	0.0417	40.94	1.153	10,000	8%
Couple	0.0418	39.59	1.840	15,000	8%

suitable threshold value. The correlation crossing this threshold is considered to be representing the seed of the mark with which embedding is performed. Fig. 4 shows the correlation when evolved PSF is not used in detection phase see (6), whereas Fig. 3 shows the same when PSF is used in the detection phase see (14).

B. Perceptual Shaping Function:

Fig. 5 show the histogram of the GP evolved PSF. It is obtained for Lena image of size 512×512 with $L = 25000$ and $G = 16000$. Using the evolved PSF, suitable SNR values are obtained for different standard images with MSS approximately equal to 0.0417. The important property of this PSF is that it is cover-image dependent and thus makes the watermarking scheme an image adaptive one. This fact can be observed from Table II, where we have used the same PSF for different standard images. It provides high image quality measures while still offers effective resistance against Gaussian noise and JPEG compression. The best evolved PSF using GP simulation is given as:

$$\alpha = \text{divide}(\text{minus}(\cos(\sin(\cos(\sin(0.62621))))), \dots, 0.58698), \cos(\cos(\cos(\cos(DCTcoef))))'$$

where $DCTcoef$ is the DCT coefficient being altered.

C. Survival Against Attacks

Fig. 6 and Table III confirm the robustness of our watermarking technique against some of the hostile attacks. These are compared to the results obtained by simulating Piva's approach [3], [4]. It can be observed that our method has an edge over Piva's method in survival against attacks like JPEG compression of 8% quality, Gaussian noise of variance=14,000 and combined JPEG and Gaussian (see Table III). The response to the correct watermark can still

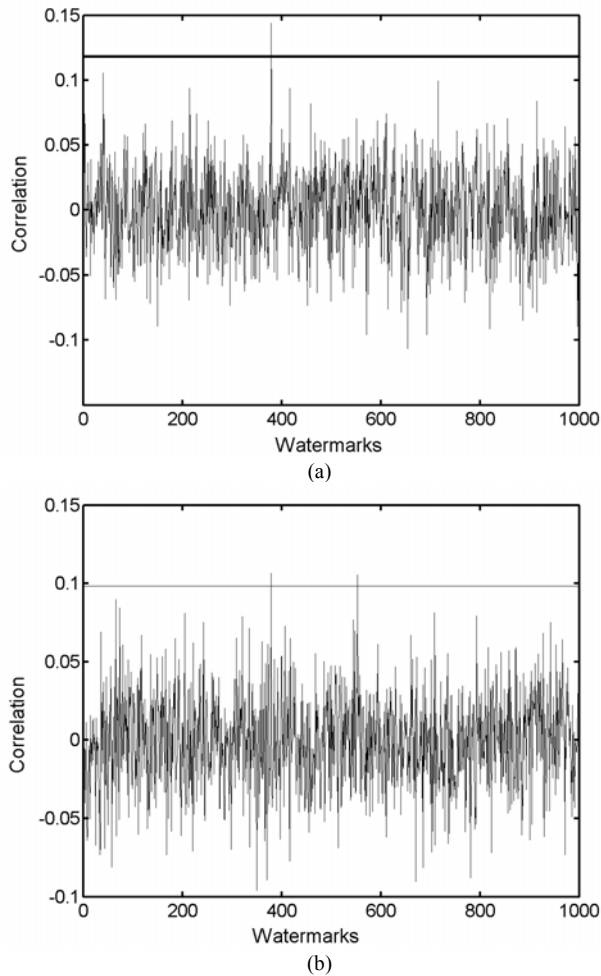


Fig. 6. (a) Detector response for 8% JPEG compression quality using our method, and (b) detector response for 8% JPEG compression quality using Piva's method.

be detected, although the image degradation is quite heavy. However like Piva's, our method is not robust against translation and rotation attacks. For this purpose, one will need to use transforms that are invariant to these types of geometric attack [21] and then use GP to evolve PSF for such domains.

Table III summarizes the performance of our watermarking approach against different attacks. Our watermarking scheme survives low-pass filtering and median filtering up to window size of 5×5 . Similarly it survives image resize up to 50%, JPEG compression up to 7% quality, Gaussian noise up to 17000 variance and combined Gaussian and JPEG compression up to 5000 variance and 25% quality respectively. As expected, with increase in Gaussian noise the threshold increases while SNR decreases.

VI. CONCLUSIONS

We have considered the robustness versus imperceptibly as an optimization problem. Using this idea, a PSF is evolved that effectively shapes the watermark according to the cover image. Unlike the heuristic techniques used in [3] that search for a constant watermarking strength for each new cover image, the PSF is image adaptive and selects a suitable watermarking strength for each DCT coefficient. The optimal/near-optimal shaping of the watermark obtained using the evolved PSF increases its resistance against most of the non-geometric attacks. As a result of

TABLE I
GENETIC PROGRAMMING PARAMETERS

Attack Name	Attack Value	MSE	SNR	T	Z
JPEG Comp.	100%	1.100	40.59	0.120	0.68
	75%	15.08	29.22	0.120	0.665
	50%	23.65	27.26	0.122	0.545
	25%	36.95	25.32	0.125	0.330
	10%	72.62	22.39	0.128	0.198
Gauss. Noise	500	449	14.19	0.190	0.750
	1000	1002	11.32	0.240	0.774
	5000	5014	5.46	0.455	0.875
	10000	10014	3.24	0.650	0.955
	15000	15045	2.64	0.790	0.998
Median Filter	2×2 window	86.33	21.61	0.110	0.454
	3×3 window	27.87	26.52	0.093	0.431
	4×4 window	102.45	20.84	0.077	0.198
	5×5 window	68.73	22.57	0.061	0.132
	6×6 window	135.44	16.61	0.060	0.132
Lowpass Filter	2×2 window	81.47	21.86	0.105	0.455
	3×3 window	49.37	24.01	0.075	0.381
	4×4 window	112.37	20.41	0.044	0.175
	5×5 window	114.65	20.30	0.032	0.065
	6×6 window	166.67	18.65	0.015	0.011
Combine Weiner, JPEG Comp. & G. Noise	$J = 75, N = 500$	109.01	0.67	0.135	0.436
	$J = 50, N = 1000$	185.0	18.54	0.164	0.490
	$J = 50, N = 5000$	842.0	12.12	0.295	0.531
	$J = 50, N = 10000$	1612.0	9.56	0.390	0.565
	$J = 25, N = 5000$	752.0	12.59	0.295	0.492
Highpass Filter	$J = 25, N = 9000$	1402.0	10.08	0.398	0.388
	3×3 window	42.34	24.81	0.172	0.410
	75%	--	--	0.121	0.468
	50%	--	--	0.072	0.164
	40%	--	--	0.083	0.050

our simulations, the best evolved PSF has been obtained. Its expression is quite general and can be used in any whole DCT domain-based watermarking technique. Work is in progress on developing perceptual shaping functions for other watermarking systems, such as spatial and block-based DCT domain.

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