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INTELLIGENT PERCEPTUAL SHAPING OF A DIGITAL WATERMARK: EXPLOITING CHARACTERISTICS OF HUMAN VISUAL SYSTEM

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Abstract

In this paper, we present a method for developing a Genetic Perceptual Model (GPM) applicable to a watermarking system. The proposed technique exploits the characteristics of human visual system using a Genetic Programming (GP) approach. We employ a tradeoff between watermark robustness and imperceptibility, as an optimization criterion in the GP search. The resultant GPM is a combination of frequency, luminance sensitivity and contrast masking, enabling us to shape the watermark according to the cover image. Our investigations have shown that the evolved GPM provides maximum allowable imperceptible alterations to the Discrete Cosine Transform coefficients of a cover image. Comparative studies in terms of watermark imperceptibility and bit correct ratio performance have been carried out. The performance of the GPM has been analyzed for various watermarking schemes.

***Keywords**:* Watermarking, Genetic Programming, Perceptual Model, Human Visual System (HVS), Discrete Cosine Transform (DCT), Spread Spectrum and JPEG.

1. Introduction

Digital watermarking is being envisaged as a promising solution to the increasing concern of protecting intellectual property rights. It is considered as the practice of imperceptibly altering data to embed a message about that data [1]. It is suitable for several applications including, copyright protection, broadcast monitoring, integrity control and copy protection. Many digital watermarking techniques have been proposed and their details can be found in the literature [1, 2, 3]. Typical watermarking schemes are based on transform-domain techniques (DCT, wavelets etc) [4, 5, 6, 7, 8] as well as spatial-domain methods [9, 10]. Transform-domain techniques have the convenience of allowing us the direct understanding of the content of the cover data.

In watermarking, one has to make a tradeoff between watermark imperceptibility and robustness. For this purpose, different methods, both in spatial as well as transformed domain, have been used to tailor a watermark according to the cover image [4, 5, 6, 10, 11]. These watermarking systems are known to be image adaptive. On the other hand, most of the earlier approaches are not image adaptive and use a global watermarking strength for all of the selected coefficients [7]. However, development of an adaptive watermarking scheme to tailor a watermark requires the understanding of the cover image in the context of HVS. Recent survey by Cox et al. [3], foresee optimal perceptual shaping of a watermark as a fruitful new area of research. The better a perceptual model is, the better is the perceptual shaping and hence imperceptibility of the watermark.

In watermarking schemes based on DCT-domain techniques, mostly Watson's Perceptual Model (WPM) [12, 13] is used to shape the watermark. WPM is based on Ahumada's work [14] and has been used in DCT-based JPEG compression. Podilchuk et al. [4, 15], using WPM, have attempted to exploit HVS for watermark shaping in DCT domain. Hernandez et al. [5] and Briassouli et al. [6] have applied the same idea in spread spectrum-like DCT domain watermarking. Cox et al. [8] have also used WPM for perceptually shaping the watermark in their informed coding and embedding based watermarking technique. WPM, although widely used in DCT domain-based watermarking, is not the optimal perceptual model [1]. Firstly, the model is built on empirical studies and is not based on extensive search methods. Secondly, it neglects certain effects, like spatial masking in frequency domain [5].

As regards spatial-domain based watermarking schemes, Delaigle et al. [9], have used both masking and texture discrimination to embed high strength watermark. On the other hand, Voloshynovskiy et al. [10] have used the idea of noise visibility function to shape the watermark in the spatial-domain. They use a non-stationary Gaussian stochastic model to model noise and thus differentiate between smooth and noisy regions in a cover image. Recently Kutter et al. [16] have presented a perceptual model that takes into account the sensitivity and masking behavior of HVS, by means of a local isotropic contrast measure and a masking model. On the other hand, Lambrecht et al. [17] have proposed a perceptual model that is based on Gabor filters.

Although, both in transform and spatial-domain based watermarking schemes, a number of efforts have been made to appropriately shape a watermark according to the cover image. However, very few attempts have been made to consider the watermark shaping as an optimization problem. Huang et al. [10, 18] have used Genetic Algorithm to choose optimal embedding positions in a block of a block-based DCT domain watermarking system. However, they have not considered the optimization of perceptual model itself to improve the marked image quality. Cox et al. [1] have used Lagrange optimization for optimally embedding an already shaped watermark. Pereira et al. [19], using Linear Programming, optimally embed a watermark in transform-domain, subject to a linear set of constraints in spatial-domain. We address these issues through the following contributions:

1. We concentrate on the optimization of the perceptual model itself and propose a technique for developing Genetic Perceptual Model (GPM).
2. We consider the perceptual model as a function and the characteristics of HVS as independent variables. The GP search mechanism is then used to strive for optimal dependency of the perceptual model on the characteristics of HVS.

Our present work, based on block-based DCT-domain is an extension of our previous work [20], in which we have concentrated on optimal shaping of a digital watermark for the whole DCT-domain based watermarking scheme.

In section 2, we discuss perceptual shaping of a digital watermark and WPM in particular. Section 3 discusses measures of estimated robustness and imperceptibility to compare the performance of both perceptual models. Section 4 describes our proposed technique for developing GPM. It also includes description of the testing and comparison phase of the best-evolved GPM. Section 5 gives implementation details. Results and discussion are described in section 6, while conclusions are given in section 7.

2. Perceptual Shaping of a Digital Watermark

Watermark of high strength is usually embedded in areas of cover work, where it is not easily discernable . This type of strategy is called as perceptual shaping of a watermark [1]. To perceptually shape a watermark, usually, perceptual models that are used in compression techniques are employed. These perceptual models are able to learn the content of a cover image by exploiting the sensitivities/insensitivities of an HVS. They take advantage of frequency sensitivity models that are based on viewing conditions as well as the cover image dependent, luminance sensitivity and contrast masking effects. Frequency sensitivity describes the HVS sensitivity to sine wave gratings at different spatial frequencies and depends only on the surrounding conditions. Luminance sensitivity on the other hand, is a measure of the effect of detectability threshold of a signal on a constant background. It depends on the average luminance value of the background as well as on the signal's luminance level. In block-based DCT case, the DC coefficient of each block dictates the luminance sensitivity for that block. The third important property of HVS that is exploited for hiding a watermark is the contrast masking. It represents the detectability of one signal in presence of another signal. This masking (hiding) effect increases when the masking signal and the signal to be masked have same spatial frequency, orientation and location. In block-based DCT, the AC coefficients dictate this behavior. In our present investigations, we are comparing the developed GPM with that of WPM.

2.1 Watson's Perceptual Model (WPM)

Let $\mathbf{x}$ represents an image matrix in spatial domain. This image is transformed to matrix $\mathbf{X}$ by applying 8x8 block DCT. According to the WPM, we define the visibility threshold $T(i,j)$ for every (i,j) DCT coefficient of 8x8 block as follows:

$$\log T(i,j) = \log\left(\frac{T_{\min}\,(f_{i,o}^2 + f_{o,j}^2)^2}{(f_{i,o}^2 + f_{o,j}^2)^2 - 4\,(1-r)\,f_{i,o}^2 f_{o,j}^2}\right) + u\left(\log\sqrt{(f_{i,o}^2 + f_{o,j}^2)} - \log f_{\min}\right)^2 \qquad (1)$$

where $f_{i,o}$ and $f_{o,j}$ denotes the vertical and horizontal frequencies (cycles/degree) of the DCT basis functions respectively. $T_{\min}$ is the minimum value of $T(i,j)$ corresponding to $f_{\min}$. The rest of the parameters are also set empirically [12-13]. The effect of luminance sensitivity is considered by correcting this threshold corresponding to average luminance of each block:

$$T'(i,j) = T(i,j)\left(\frac{X_{o,o}}{\overline{X}_{o,o}}\right)^{a_T} \qquad (2)$$

where $X_{o,o}$ is the DC coefficient of each block and $\overline{X}_{o,o}$ represents the average screen luminance =1024 (for an 8-bit image). The effect of contrast masking is incorporated by the following relation:

$$T^*(i,j) = \max\left[\,T'(i,j)\ ,\ \left|T'(i,j)\right|^{1-\omega} X(i,j)^{\omega}\,\right] \qquad (3)$$

where $X(i,j)$ is AC DCT coefficient of each block and ω has been empirically set to a value of 0.7. These allowed alterations represent the perceptual mask denoted by $\boldsymbol{\alpha}$.

3. Watermark Robustness and Imperceptibility Measures

Imperceptibility of a watermark is usually assessed through the quality of the watermarked image, which is evaluated based on the objective measures, including Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR), weighted Peak Signal to Noise Ratio (wPSNR) [11], Watermark to Document Ratio (WDR) [25] and Structural Similarity Index Measure (SSIM) [21]. SSIM measure uses the hypotheses that HVS is highly adopted for extracting structural information. It is argued that natural image signals are highly structured, as the nearby pixel exhibit strong dependencies [21]. These dependencies provide information about the structure of the object in an image, which are overlooked by the error-based measures. To estimate robustness during GP simulation, we use watermark power. We represent watermark power by Mean Squared Strength (MSS) given as:

$$MSS = \frac{1}{N_b N_d} \sum_{u_1=1}^{N_b} \sum_{u_2=1}^{N_d} \alpha(u_1, u_2)^2 \tag{4}$$

where, N_b is the total number of 8×8 blocks in the cover image and N_d is the number of bandpass (low and mid frequency) DCT coefficients in a block.

We have used watermark power as an estimate of robustness, because in the testing and comparison phase of best evolved GPM (section 4.3), the underlying watermarking technique remains the same for both WPM and GPM based perceptual shaping schemes. Hence, as in our previous work [20], we assume that the MSS will provide a suitable measure of the *estimated robustness* at the embedding stage of the GP simulation.

4. Proposed Technique for Developing a GPM

Figure 1 shows the basic architecture of our proposed scheme for developing perceptual model. Three different modules supplement each other in a cyclic fashion. Robustness versus imperceptibility tradeoff is considered as an optimization problem. We first explain the overall working of the basic architecture. Details of the individual modules are given in section 4.1.

The GP module produces a population of GPM. Each GPM is presented to the perceptual shaping module, where it is applied on the cover image in DCT-domain, generating a perceptual mask. The watermark is shaped using the perceptual mask and its imperceptibility is then used as a scoring criterion in the GP module. In this way, the GP module evaluates the performance of its several generated GPMs. In a separate stage, the best-evolved GPM is compared with that of the WPM.

Figure 1 goes here

4.1 Evolution of Perceptual Models

4.1.1 The GP Module

Genetic Programming, an intelligent search technique, has found numerous applications in the last decade [22]. It is based on the mechanism of natural selection and natural genetics. In GP, a candidate solution is represented using a data structure such as a tree. Initially, a random population of such candidate solutions is created. Every candidate solution is evaluated and scored using application dependent fitness function. The survival of fittest is implemented by retaining the best individuals. The rest are deleted and replaced by the offspring of the best individuals. The retained ones and the offspring make a new generation. Some offspring may have high score than their parents in the previous generation. The whole process is repeated for the subsequent generations. With the scoring and selection procedure in place, each new generation has, on average, a slightly higher score than the previous one. The process is stopped when a single individual in a generation gets a score that exceeds a desired value. In this way the solution space is refined generation by generation and thus converges to the optimal/near optimal solution. For a detailed study one may refer to [22, 28]. In this present work, we search for optimal perceptual models—perceptual models that are able to make optimal tradeoff between robustness and imperceptibility with respect to existing tradeoff techniques.

To represent a possible solution with a GP tree, one needs to define suitable functions, terminals, and fitness criteria according to the optimization problem. These settings for evolving GPM are as under:

<u>*GP Function Set:*</u> Function set in GP is a collection of functions available to the GP system. In our GP simulations, we have used simple functions, including four binary floating arithmetic operators (+, -, *, and protected division), *LOG, EXP, SIN* and *COS*.

<u>*GP Terminals*</u>*:* To develop initial population of GPM, we consider GPM as watermark shaping function and the characteristics of HVS as independent variables. By doing this, in essence, we are letting GP exploit the search space representing different possible forms of dependencies of the watermark shaping function on the

characteristics of HVS. Therefore, visibility threshold $T(i,j)$, DC and AC DCT coefficients of 8x8 block are provided as variable terminals (equation 7 and figure 2). Random constants in the range [-1,1] are used as constant terminals.

Figure 2 goes here.

Fitness Function: A fitness function in GP is supposed to grade each individual of the population. It is designed to provide feedback about how well an individual of the GP population is performing at the given task. Figure 4 depicts the idea of using fitness function as feedback. Every perceptual model of a GP population is evaluated in terms of structuring the watermark. The evaluation is based on how well is the SSIM measure at a certain level of *estimated robustness* (MSS).

$$Fitness = SSIM_{E.R} \tag{5}$$

Thus, each individual perceptual model of a GP population is scored using equation 5 as a fitness function. The greater the fitness is, the better the individual has performed.

Termination Criterion: The GP simulation is ceased when one of the following conditions is encountered:

1. The fitness score exceeds 0.99 with $MSS \geq 20.0$.
2. The number of generations reaches the predefined maximum number of generations.

4.1.2 Perceptual Shaping Module

A perceptual model exploits the characteristics of HVS to tailor a watermark according to the cover image. This enables us to embed a large energy watermark at low cost of resultant distortion to the cover image. The perceptual shaping module receives the individual GPM provided by the GP module as an input. Each GPM is operated on the cover image in DCT-domain. Corresponding to the selected DCT coefficient of a block, the GPM returns a value. The magnitude of this value represents the perceptual strength of the alteration made to that coefficient. The functional dependency of the perceptual model on the characteristics of HVS can be represented as follows:

$$\alpha(k_1, k_2) = f\left(T(i, j),\ X_{0,0},\ X(i, j) \right) \tag{6}$$

where the first variable, T is the visibility threshold representing frequency sensitivity of HVS. $X_{0,0}$ is the DC DCT coefficient, while $X(i, j)$ is the AC DCT coefficient of the current block. They represent the luminance sensitivity and contrast masking characteristics of HVS respectively.

Operating the GPM on all of the DCT coefficients, we obtain the perceptual mask for the current cover image. The product of the spread-spectrum sequence and expanded message bits is multiplied with this perceptual mask to obtain the watermark. The 2-D watermark signal $\mathbf{W}$ (see figure 3) is given as:

$$\mathbf{W} = \boldsymbol{\alpha} \cdot \mathbf{S} \cdot \mathbf{b} \tag{7}$$

where $\mathbf{S}$ is a pseudo random sequence and $\mathbf{b}$ is the repetition-based expanded code vector, corresponding to the message to be embedded. The embedding is performed by adding this watermark to the original image in transformed domain:

$$\mathbf{Y} = \mathbf{X} + \mathbf{W} \tag{8}$$

Here the watermark $\mathbf{W}$ is our desired signal, while the cover image $\mathbf{X}$ acts as an additive noise. As we are developing GPM, therefore, equation 8 will be modified as follows:

$$\mathbf{W} = \boldsymbol{\alpha}_G \cdot \mathbf{S} \cdot \mathbf{b} \tag{9}$$

where $\boldsymbol{\alpha}_G$, representing perceptual mask corresponding to GPM, incorporates the dependencies from visibility threshold $T(i,j)$, AC and DC coefficients.

Figure 3 goes here.

4.1.3 Watermarking Module

In order to evaluate the performance of each individual GPM of the GP population, the watermarking module implements the spread spectrum based watermarking technique proposed by Hernandez et al. [5] (see figure 4). This watermarking technique is oblivious and embeds message into the low and mid frequency coefficients of 8×8 DCT blocks of a cover image. The employed watermarking scheme performs the statistical modeling of DCT coefficients using generalized Gaussian distribution. This fact helps in constructing better detector/decoder structures than the simple Gaussian correlation receiver that is mostly used. One of the reasons for using this watermarking scheme is that the DCT is applied in blocks of 8x8 pixels, in a manner similar to that used in JPEG algorithm. Hence, it is easy to use and compare WPM with that of the GPM. Secondly, this watermarking scheme has strong theoretical foundations [5]. The embedding in DCT-domain is performed using equation 8.

The watermarking module of our proposed technique provides the imperceptibility of the resultant watermark as a feedback to the GP module. The structure of how different sub-modules work within the proposed model is shown in figure 3.

Figure 4 and 5 go here.

4.3 Testing Performance of the Best-evolved GPM

In order to assess the performance of the best-evolved GPM, its expression is saved at the end of the GP simulation. The best-evolved GPM is then compared with that of WPM in terms of watermark shaping. Where by, the watermark shaping ability is assessed by computing watermark imperceptibility as well as robustness measures. Figure 5 shows the details of the testing method for the evolved GPM using watermarking approach of [5]. In this testing phase, besides using the watermarking approach proposed in [5], we also use an algorithm similar to the E_PERC_SHAPE algorithm of Cox et al. [1] as well. We compare both perceptual models on the E_PERC_SHAPE algorithm, to see whether the GP search mechanism has a bias towards Hernandez's watermarking algorithm used during evolution stage. We also evaluate the message retrieval performance in terms of Bit Correct Ratio:

$$BCR(\mathbf{M},\mathbf{M}') = \frac{\sum_{i=1}^{L_m} \overline{(m_i \oplus m_i')}}{L_m} \tag{10}$$

where $\mathbf{M}$ represents the original, while $\mathbf{M}'$ represents the decoded message, L_m is the length of the message and $\oplus$ represents exclusive-OR operation. It should be noted that $(1-BCR)$ represents bit incorrect ratio.

5. Implementation Details

We have used MATLAB environment for our experimental studies. To employ GP, we use GPLAB toolbox [36-37]. The GP parameter settings are shown in table 1, while the remaining parameters are used as default in the software.

Lena image of size 256x256 is used as a cover image with $N_d = 22$ (7 to 29 in zigzag order) during the GP simulation. Message size is kept equal to 64 bits. Following [12, 13], the parameters of WPM are set as $r = 0.7$, $T_{\min} = 1.1548$, $u = 1.728$, $f_{\min} = 3.68$ cycles/degree and $a_T = 0.649$. To estimate the value of parameter c for generalized Gaussian Distribution-based modeling of each (i,j) DCT sequence [5], we have considered its range [0.02, 2.0] with grid step of 0.02. The watermark power, represented by MSS, is constrained to lie above a certain lower bound (e.g. 20.0) for all the individuals.

In the testing phase, all images except Baboon and Boat are of size 256x256. For each of the test image, grid search with a step of 0.01 is applied to find the watermark strength needed to produce a resultant image of same SSIM measure. In order to develop GPM, keeping population size equal to 300 and no. of generations 30, the GP simulation consumes about half an hour on a Pentium IV machine (2.0 GHz speed and 256 Mb RAM). In the testing phase, the watermarking scheme using the best-evolved GPM spends about 30 sec to watermark Lena image.

Table 1 goes here.

6. Results and Discussion

6.1 Perceptual Shaping Using GPM

In figure 6, watermarking strength corresponding to each bandpass DCT coefficient of block-based DCT is shown. These strengths are produced by the GPM for Lena image. It is observed that depending upon the current AC and the DC coefficient; it provides suitable imperceptible alterations according to the spatial content of that block. This fact indicates that GPM is able to exploit HVS for shaping the watermark according to any cover image. In other words, GPM makes the watermarking technique adaptive with respect to the cover image. The resultant watermark is shown in figure 7.

Figure 6 and 7 go here.

6.2 Imperceptibility of the resultant watermark

In figure 10, we have shown the difference image, obtained by subtracting the original image (figure 8) from the watermarked image (figure 9) in spatial domain. The pixel intensity of the difference image is amplified ten times for illustration purpose. Although, DCT domain is used for embedding, still GPM is able to learn the spatial distribution of the Lena image, as most of the strong embedding is performed in highly textured areas.

Figure 8, 9 and 10 go here.

Table 2 compares both perceptual model in terms of the marked image quality, *estimated robustness* and BCR performance for 10 different standard images. Both perceptual models are multiplied with some scaling factor to achieve a desired Value of SSIM that represents watermark imperceptibility. Columns 3 of table 2 and table 3 represents watermark strength, while column 4 represents mean squared strength giving a measure of the watermark power. On the other hand, columns 5-6 show watermarked image quality in terms of different measures. These different image quality measures are used here due to two reasons. Firstly, it would be easier for other researchers to verify our results. Secondly, because of the complexity in modeling HVS, there is no generic and widely accepted image quality measure reported so far [21]. Therefore, we use these different measures; however, most of our watermark imperceptibility analysis is based on the most recently reported SSIM measure [21].

It is observed that in case of GPM, keeping same distortion of the resultant image as in WPM case, the watermark being embedded is of high power. Specifically, by looking at the MSS values (column 4 of table 2), GPM is able to embed watermark of approximately double power, as compared to that of WPM. This improvement in terms of high power embedding can be observed for all of the test images and in both watermarking approaches (see table 3 as well). Consequently, the watermark shaping ability of the evolved GPM is superior to that of WPM.

Table 2 and 3 go here.

6.3 Message Retrieval Performance

Last column of table 2 shows the message retrieval performance of both the perceptual models at equal image distortion for different test images. Table 4, on the other hand, illustrates the comparison of both perceptual models in terms of BCR performance, when the message size is varied. It shows the bit extraction power of both models, when the capacity of a watermark is increased. We have multiplied both perceptual models by a scaling factor to produce watermarked image having SSIM $\geq$ 0.981 . With increase in message size, GPM produces high (1-BCR) than that of WPM. This could be mainly because equal watermark power may not result in the same practical robustness for two different perceptual shaping schemes. In other words the *estimated robustness* measure MSS does not always reflect actual robustness.

With an increase in message size, the watermarked image quality remains the same for both perceptual models. This is because, only the number of repetitions of a bit in different blocks decreases with increase in message size. The BCR performance can be increased by using advance channel coding like low-density parity check code [25] in concatenation to the simple repetitive coding that we have used. Since in this work we are concentrating on the perceptual shaping of the watermark, therefore we use repetitive coding only.

Table 4 goes here.

6.4 Best-evolved GPM

Expression of the best GPM in normal notation is:

$$\alpha(k_1, k_2) = ((|X(i,j)| - (SIN(X_{0,0}/1024)/v(i,j))) - \log(T(i,j) - 0.583018), \quad i,\ j \in \{0, \ldots.., 7\} \tag{11}$$

$$\text{where } v(i,j) = (T(i,j) - 1.4023) \cdot ((T(i,j) - 0.10025 / |X(i,j)|)$$

Figure 11 shows the accuracy versus complexity plot of GP simulation. It is observed that as generations pass by, improvement in fitness of the best individual is achieved at cost of its complexity. That is, with increase in fitness of the best perceptual model of a generation, its genome's total number of nodes as well as its average tree depth increases.

Figure 11 goes here.

7. Conclusions

We have considered the robustness versus imperceptibility tradeoff in a watermarking system as an optimization problem to obtain optimal/near–optimal GPM. The developed GPM is image independent and can be used for any cover image. It is a combination of frequency and luminance sensitivity as well as contrast masking. It offers superior performance to that of Watson's perceptual model in terms of watermarked imperceptibility but not in terms of message decoding. Our analysis shows that high power embedding does not always reflect high practical robustness. Developing GPM by employing GP needs considerable execution time (approximately half an hour). However, once the best GPM is developed, then employing GPM for watermark shaping is quite straightforward and easy to implement. Even in the development phase, using fast and parallel processing based implementations of GP [22, 26, 27], it is possible to use GP-based watermarking to real business applications. The concept of Pareto optimization [28], if applied for simultaneously improving robustness, imperceptibility as well as capacity of a watermark, may further improve the proposed method. The proposed technique can be applied in other watermarking domains, like FFT, Wavelet and Spatial as well. Currently work is in progress to enhance the proposed technique for developing GPM, by exploiting information about the conceivable attacks as well.

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TABLE 1 GP PARAMETERS SETTING

Objective:	**To evolve optimal /near-optimal Perceptual model**
Function Set:	+, -, *, protected division, *SIN, COS,* and *LOG*
Terminal Set:	Constants: *random constants in range* of [-1, 1] Variables : $X_{0,0}\ /1024, abs\ (X\ (i,j))\ and\ T(i,j)$
Fitness :	*SSIM*
Selection:	Generational
Population Size:	260
Initial max.Tree Depth	6
Initial population:	Ramped half and half
Operator prob. type	Variable
Sampling	Tournament
Expected no. of offspring	rank89
Survival mechanism	Keep best
Real max level	28
Termination:	Generation 30

Table 2 Imperceptibility and BCR comparison of WPM and GPM
(The watermarking scheme used is that of [5]. All the images, except Baboon and Boat are of size 256x256, while message size = 64)

Test Images	**Perceptual Model**	**Watermark strength**	**Watermark power**	**Watermarked image quality measures**					**Decoding performance**
		Scaling Factor	**MSS**	**MSE**	**WDR**	**PSNR**	**wPSNR**	**SSIM**	**BCR**
Lena	WPM	0.3660	13.3571	4.59020	-35.819	41.5125	44.5196	0.9809	1.0
	GPM	0.3910	27.224	9.3570	-32.726	38.4192	42.7858	0.9810	1.0
Trees	WPM	0.413	28.692	9.85670	-33.0527	38.1935	43.2628	0.9810	1.0
	GPM	0.326	52.1633	17.9278	-30.455	35.590	41.703	0.9810	1.0
Baboon (232x248)	WPM	0.504	46.876	16.0850	-29.2547	36.066	44.947	0.9810	1.0
	GPM	0.357	68.6184	23.5636	-27.596	34.408	44.023	0.9810	1.0
Couple	WPM	0.440	30.869	10.5910	-31.957	37.881	42.796	0.9809	1.0
	GPM	0.335	46.064	15.7770	-30.2267	36.1504	41.849	0.9809	1.0
Boat (232x248)	WPM	0.402	22.979	7.8730	-33.775	39.1691	43.488	0.9809	1.0
	GPM	0.331	42.9183	14.7246	-31.0567	36.4504	41.968	0.9809	0.984
Airplane	WPM	0.244	6.1794	2.1210	-42.596	44.865	46.240	0.9809	1.0
	GPM	0.417	27.153	9.3220	-36.166	38.435	41.4217	0.9810	1.0
Watch	WPM	0.259	9.286	3.187	40.748	43.097	45.577	0.9809	1.0
	GPM	0.467	53.987	18.5227	-33.4538	40.3724	42.569	0.9809	1.0
Fruits	WPM	0.331	14.3347	4.926	-37.769	41.206	44.081	0.9810	1.0
	GPM	0.381	41.854	14.367	-33.1207	36.557	41.307	0.9810	1.0
House	WPM	0.314	8.9053	3.0543	-38.3856	43.3814	45.254	0.981	1.0
	GPM	0.359	20.8086	7.127	-34.7056	39.6014	42.464	0.9810	0.984
Chemical Plant	WPM	0.473	28.246	9.7046	-31.1713	28.261	42.7097	0.9809	1.0
	GPM	0.358	39.538	13.588	-29.709	36.799	42.0516	0.9809	1.0

Table 4 BCR versus message size performance (Note that as message size increases, no. of repetitions of a bit decreases. Hence, the watermarked image distortion remains the same for all cases. Scaling factors are 0.391 and 0.366 for GPM and WPM respectfully)

Message Size	SSIM		(1-BCR)	
	WPM	GPM	WPM	GPM
64	0.981	0.981	0.0	0.0
128	0.981	0.981	0.00	0.0313
256	0.981	0.981	0.0117	0.0430
512	0.981	0.981	0.0371	0.0898
1000	0.981	0.981	0.051	0.1510

Figure 1 Basic architecture of developing GPM

Figure 2 An example GP tree representing a GPM

Figure 3 Block diagram of Developing GPM.

Figure 4 Hernandez's [5] watermark embedding scheme

Figure 5 Block diagram of the testing method using watermarking approach of [5]

Figure 6 Watermarking strength for Lena image using evolved GPM

Figure 7 Watermark generated for Lena image using evolved GPM

Figure 8 Original Lena image

Figure 9 Watermarked Lena image using evolved GPM

Figure 10 Difference image of Lena

Figure 11 Accuracy versus complexity plot of GP simulation

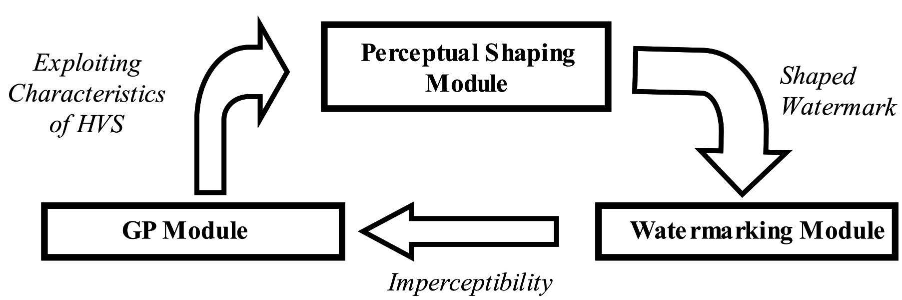

Figure 1 Basic architecture of developing GPM

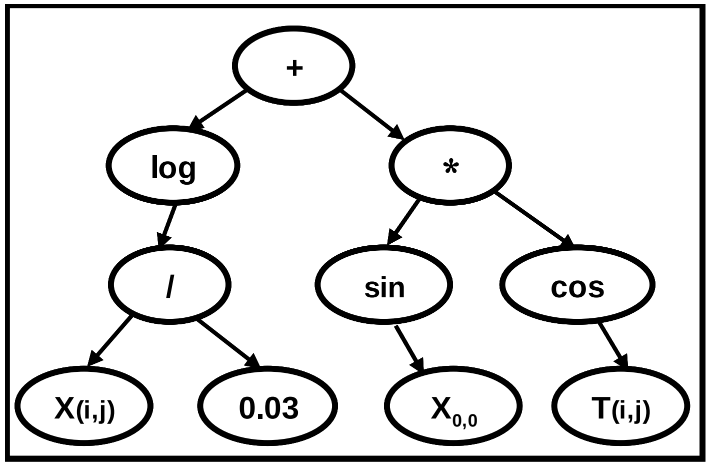

Figure 2 An example GP tree representing a GPM

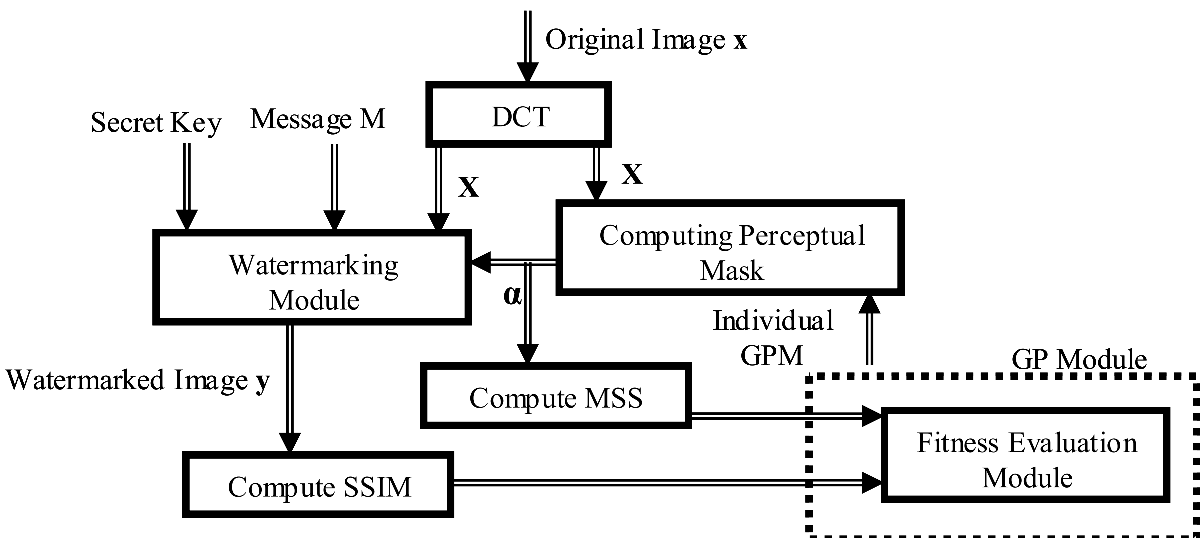

Figure 3 Block diagram of Developing GPM.

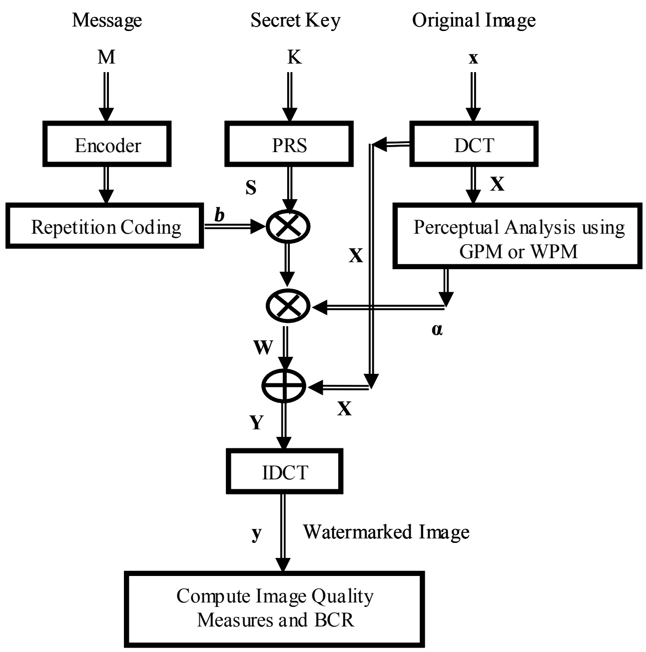

Figure 5 Block diagram of the testing method using watermarking

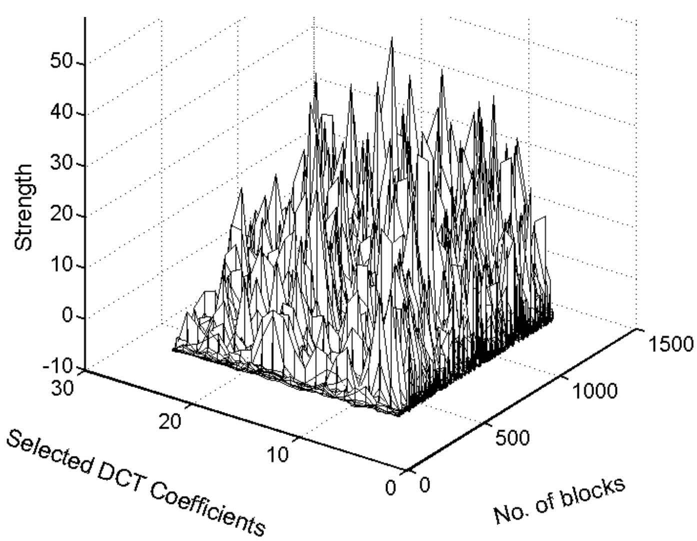

Figure 6 Watermarking strength for Lena image using evolved GPM

Figure 8 Original Lena image

Figure 9 Watermarked Lena image using evolved GPM

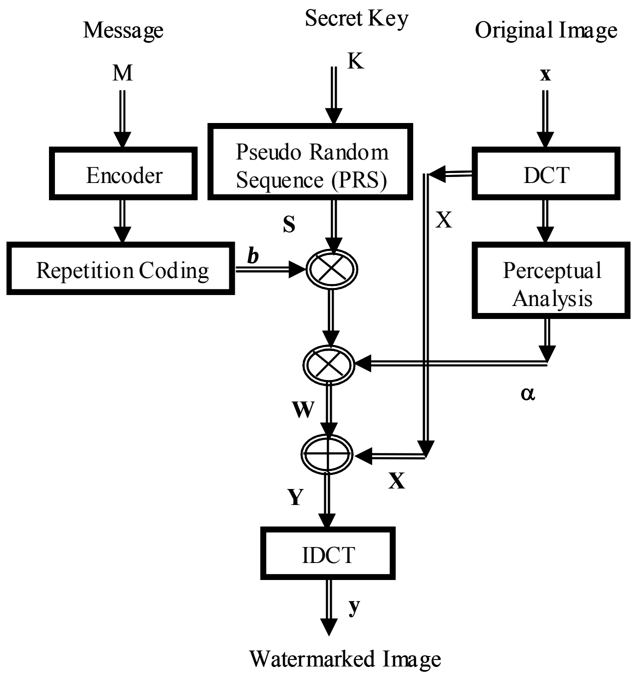

Figure 4 Hernandez's [5] watermark embedding scheme

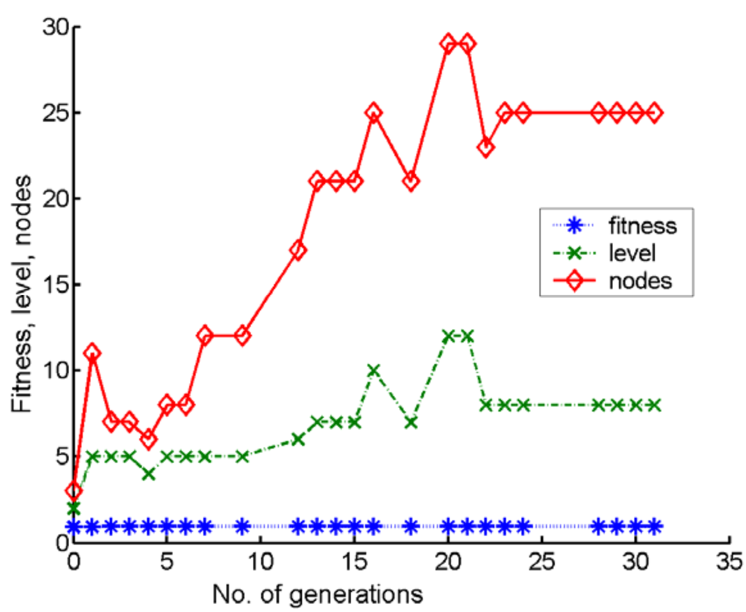

Figure 11 Accuracy versus complexity plot of GP simulation

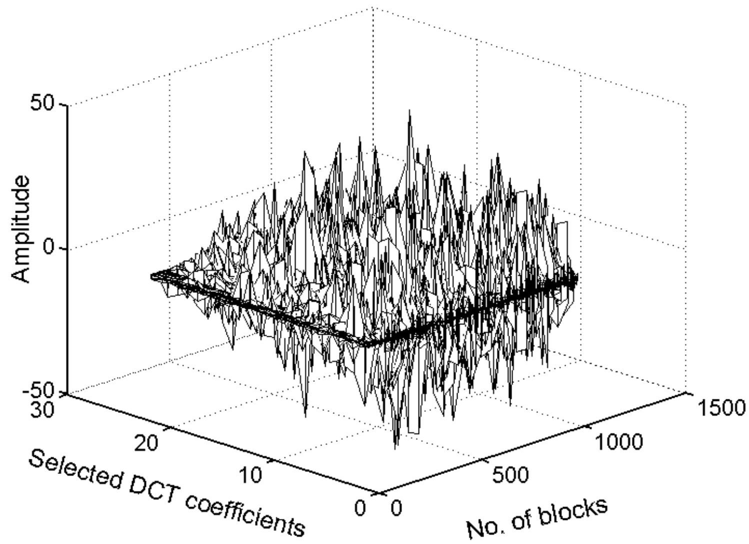

Figure 7 Watermark generated for Lena image using evolved GPM

***Answers to Revised review, "KES Journal"* (Paper Id: kesjpr05-056.)**

Title: INTELLIGENT PERCEPTUAL SHAPING OF A DIGITAL WATERMARK: EXPLOITING CHARACTERISTICS OF HUMAN VISUAL SYSTEM

Reviewer 2.

1. The meaning of the different values in the tables are not explained

Answer:

- *As suggested, the meaning of the different measures and their usage has been explained now (see section 3, Para 2 of page5, section 6.2, page 11) .*

2. Especially the meaning of MSS and MSE should be better described

Answer:

- *MSS has been defined in equation 4, page 5, while MSE has been explained in first line of section3 and second Para of section 6.2.*

3. The table with the data are not easily readable

Answer:

- *As suggested, the table headings have been further extended to convey more information to the reader (see table 2 and table 3).*

4. Concluding remarks are not easily readable.

Answer:

- *As suggested the conclusions has been modified to make it more lucid(see section 7, page 13).*