A GA-BASED JOINT CODING AND EMBEDDING OPTIMIZATION FOR ROBUST AND HIGH CAPACITY IMAGE WATERMARKING*

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ABSTRACT

A new informed image watermarking algorithm is presented in this paper, which can achieve the information rate of 1/64 bits/pixel with high robustness. Firstly, a LOT (Local Optimal Test) detector based on HMM in wavelet domain is developed to tackle the issue that the exact strength for informed embedding is unknown to the receiver. Then based on the LOT detector, the dirty-paper code for informed coding is constructed and the metric for the robustness is defined accordingly. Unlike the previous approaches of informed watermarking which take the informed coding and embedding process separately, the proposed algorithm implements a joint coding and embedding optimization for high capacity and robust watermarking. The genetic algorithm (GA) is employed to optimize the robustness and distortion constraints simultaneously. Experimental results show that the proposed algorithm achieves significant improvements in performance against JPEG, gain attack, low-pass filtering and etc.

Index Terms**—**image processing, wavelet transforms, signal detection, hidden Markov model.

1. INTRODUCTION

Watermarking can be treated as the process of communication with side information. The informed watermarking with the original cover work as side information can be used to design the robust watermarking algorithm with high capacity, and becomes the domain of intensive research [2-7].

The conventional informed watermarking [2-3] includes two separate stages, i.e., informed coding and embedding. The use of dirty–paper code is the most common approach to informed coding, where the set of codewords is divided into different cosets, which contain multiple codewords representing the same message. And the coding depends on the cover work in which the message will be embedded. In informed embedding, the embedding process tails each watermark code according to the cover work, attempting to achieve the optimal trade-off between perceptual fidelity and robustness. Usually, a correlation-based detector is employed to incorporate the informed watermarking process [2-3].

Instead of the correlation-based one, a HMM based detector is developed in our previous work [9] with significant performance improvement. For blind detection in the framework of informed watermarking, the actual strengths for informed embedding are unavailable to the receiver, and consequently the performance of HMM based detector is degraded considerably. Therefore, a new detector, namely LOT (Locally Optimum Test), is developed to tackle the issue of blind watermark detection. The LOT detector is derived from HMM model by application of hypothesis testing theory [10]. The HMM LOT detector is then used to design the dirty-paper code and define the robustness metric for the proposed informed watermarking algorithm.

With the nonlinear HMM-based LOT detector, the informed watermarking can no longer be treated as two separate process of coding and embedding. For a given message, the code determined from informed coding is not necessary the optimal one for informed embedding, and vice versa. Therefore, an algorithm of joint coding and embedding optimization is proposed. And the genetic algorithm (GA) is employed to optimize the robustness and distortion constraints simultaneously. Simulation results demonstrate that the proposed algorithm can achieve information rate as 1/64 bits/pixel with high robustness against JPEG, Gaussian noise, gain attack and etc.

The remainder of this paper is organized as follows. In section 2, the LOT detector is developed and analyzed, which is utilized to design the dirty-paper code in section 3. The GA based joint coding and embedding optimization for informed watermarking is given in section 4. Simulation results are given in section 5. And the conclusion is drawn in section 6.

2. HMM- BASED LOT DETECTOR

Let $\mathbf{w} = \left(w_{j,l}^{1} w_{j,l}^{2} w_{j,l}^{3}\right)^{T}$ denote a *vector node* that consists of the wavelet coefficients at level *j* and location *l* in orientation *d* (*d*=1, 2, 3 for H, V and D, respectively), If only the coarsest 2-level wavelet pyramids are considered, then totally 5 vector nodes $\mathbf{w}_k$ (k $= 0, 2, \ldots, 4$) are defined (The 3 nodes with the same label in Fig.1 constitute a vector node), which forms a 15-node vector tree as shown in Fig.1. To characterize the statistical dependency of wavelet coefficients, a vector DWT-HMM model [9] with a set of parameters Θ is developed,

$$\mathbf{\Theta} = \{\mathbf{p}_1, \mathbf{A}_2, \ldots, \mathbf{A}_J; \mathbf{C}_j^{(s)}, (j = 1, \ldots, J, s = 1, 2)\}. \quad (1)$$

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With the vector HMM model, the pdf of the vector node $\mathbf{w}_k(\mathrm{k}=0,2,\ldots,4)$ can be expressed as:

$$f(\mathbf{w}_k)=p_j^{(1)}g(\mathbf{w}_k;\mathbf{C}_j^{(1)})+p_j^{(2)}g(\mathbf{w}_k;\mathbf{C}_j^{(2)}) \qquad (2)$$

where $p_j^{(1)}+p_j^{(2)}=1$ and $g(\mathbf{w};\mathbf{C})=(1/\sqrt{(2\pi)^n\left|\det(\mathbf{C})\right|})\exp(-\mathbf{w}^T\mathbf{C}^{-1}\mathbf{w}/2)$. Hence, the pdf of a vector tree $\boldsymbol{T}$ can be constructed as

$$f(\mathbf{T}\mid\Theta)=\prod_{k=0}^{4}f(\mathbf{w}_k)\,. \qquad (3)$$

If a 15-element codeword **CW** is embedded into the vector tree **T** and the watermarked vector tree is $\mathbf{T}_w$, then the pdf of $\mathbf{T}_w$ is

$$f(\mathbf{T}_w\mid\mathbf{CW})=f(\mathbf{T}_w-\mathbf{B}\cdot\mathbf{CW}\mid\Theta) \qquad (4)$$

where **B** stands for 15-element embedding strength.

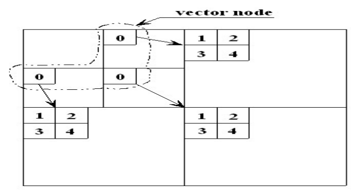

Fig.1 Vector DWT-HMM model (2 levels)

Unlike the previous approach in [9] where the vector **B** used in HMM detector is the HVS (Human Visual System) masking value and known to the detector, the actual embedding strength for the proposed informed watermarking algorithm is unavailable to the detector, and consequently the performance of the detector is degraded considerably. To tackle this issue, the HMM based LOT (Locally Optimum Test) detector is developed by applying the theory of hypothesis testing [10]:

$$L(\mathbf{T})_{LOT}=-\frac{f'(\mathbf{T})}{f(\mathbf{T})}=\prod_{k=0}^{4}(\prod_{i=1}^{3}V_{LOT}(k,i)) \qquad (5)$$

where $V_{LOT}(k,i)$ is further defined as :

$$V_{LOT}(k,i)=-\frac{f'(\mathbf{w}_k)}{f(\mathbf{w}_k)}\cdot\mathbf{CW}(k,i),\ i=1,2,3. \qquad (6)$$

The $\mathbf{CW}(k,i)$ in (6) denotes the code element of **CW** that is corresponding to the i^{th} element of the vector node $\mathbf{w}_k$, and $f'(\mathbf{w}_k)$ is the partial derivative of $f(\mathbf{w}_k)$. With the HMM based LOT detector in (5), the embedding strength **B** is no longer necessary for the detection of codeword **CW** in vector tree $\mathbf{T}_w$. To simplify the complexity of computation, the log-form LOT detector is often used and defined as:

$$L'(\mathbf{T})_{LOT}=\sum_{k=0}^{4}(\sum_{i=1}^{3}sign(V_{LOT}(k,i))\cdot\log(1+\left|V_{LOT}(k,i)\right|) \qquad (7)$$

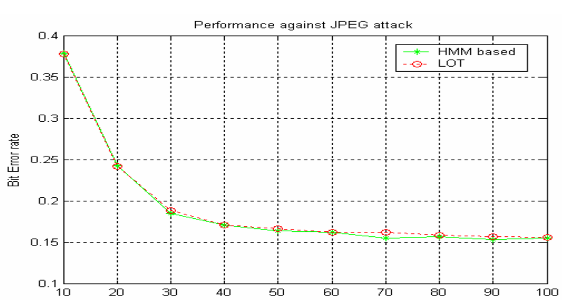

Fig.2 Performance comparison between the HMM-based detector and the LOT detector

To evaluate the performance of the proposed LOT detector, a 60 bits watermark is embedded into the *512*512*8b* standard image "Lena" with the algorithm in [9] and then detected with both the HMM based detector in [9] and the LOT. The performance comparison in Fig.2 shows that the proposed LOT detector has almost the same performance as the HMM based detector in [9].

3. DIRTY-PAPER CODE DESIGN

The vector tree in Fig.1 is used as the carrier for watermark message, and the codeword thus has 15 elements too. With m bits messages to be embedded into every tree, $M=2^m$ cosets need to be constructed according to the principle of dirty-paper coding, each of which has multiple codewords so that one can choose a best one according to the given carrier to obtain the optimal trade-off between the robustness and imperceptibility. To achieve this target, the codewords should be diverse enough so as to easily adapt to different carriers; on the other side, the minimum distance among the codewords in different coset should be also kept as large as possible when considering the definition of LOT detector in (5) and (6) and in the interest of robust detection.

For the two-level vector tree shown in Fig.1, a hierarchical construction of the dirty-paper code is developed based on both the robustness analysis in [9] and the principles of dirty-paper coding. Codes from different coset are designed to have a relative large distance between the 3 code elements corresponding to the parent node since the parent nodes in a vector tree would have more contribution to robust detection than their four children [9]. In addition, based on the results in [9] and the features of dirty-paper coding, a diversity configuration for the code elements corresponding to the children nodes would help to trade off the robustness and invisibility. Therefore, for the code elements corresponding to each four children with the same parent, two of them are set to be positive and others are negative. The above two rules are employed in the process of dirty-paper design.

The proposed algorithm embeds 1 bit message to every 15-node vector tree. Therefore, two cosets corresponding to message 0 and 1 are to be designed. Let N denotes the code number in a coset, the dirty-paper code are constructed as follows:

(1) For coset 0, the 3 code elements corresponding to parent nodes are set to be $\{a+r_1 \quad a+r_2 \quad a+r_3\}$; while for coset 1, the 3 ones are set to be $\{-a-r_4 \quad -a-r_5 \quad -a-r_6\}$, where a is positive integer and set as 1 in our design, and $r_i(i=1\cdots6)$ is a random number in the range (0,1);

(2) As shown in Fig.1, every vector tree consists of 3 sub-trees at orientation d (d=1, 2 and 3 for H, V and D, respectively). Let $c_i^{d,m}$ denotes the code element corresponding to coset $m(m=1,2)$, orientation $d(d=1,2,3)$, and children $i(i=1\cdots4)$. Then in the case of $d=1$, for coset 0, $\{c_1^{1,0} \quad c_2^{1,0} \quad c_3^{1,0} \quad c_4^{1,0}\}$ is set to be $\{a+s_1 \quad a+s_2 \quad -a-s_3 \quad -a-s_4\}$; while for coset 1, $\{c_1^{1,1} \quad c_2^{1,1} \quad c_3^{1,1} \quad c_4^{1,1}\}$ is set to be $\{-a-s_5 \quad -a-s_6 \quad a+s_7 \quad a+s_8\}$, where $s_i(i=1\cdots8)$ is a random number in (0,1). The same design rule can be applied to the case of $d=2,3$.

4. GA-BASED INFORMED WATERMARKING

Informed Watermark

The image is firstly decomposed into the 3-level wavelet pyramid, and then the coarsest two levels (scale=2 and 3) are used to construct the vector trees (see Fig.1) which are used as the carriers of watermark message. For each vector tree, 1 bit message is informedly coded and embedded, which leads to an information rate as 1/64 bits/pixel. For informed coding, two cosets with size *N*, namely C_0 and C_1, are constructed with the method described in section 2; for informed embedding, the GA algorithm is employed so as to obtain the optimal embedding strength under the robustness and distortion constraints. As the nonlinear feature of HMM-based LOT detector, a strategy of joint coding and embedding optimization is required to further trade-off the robustness and invisibility constrains simultaneously. More specifically, the informed watermarking is implemented as follows:

(1) Determine the coset $C_i\ (i=0,1)$ according to the to-be-embedded bit $b\ (b=0,1)$;

(2) Select a codeword $\mathbf{CW}_n^i$ ($n=1,2,\ldots,N$) from C_i orderly;

(3) For a given vector tree $\mathbf{T}$, deploy the GA algorithm to seek an optimal 15-node embedding strength **B** under constrain of the robustness and distortion, which put the vector tree to the detectable area of $\mathbf{CW}_n^i$. The formulation of GA algorithm will be given in the next sub-section;

(4) With the generated **B** for $\mathbf{CW}_n^i$, the robustness to distortion ratio $RDR=\Delta R/\Delta D$ is computed;

(5) Go to step (2) until all codewords in C_i are proceeded. The codeword, namely, $\mathbf{CW}_{opt}^i$, with maximum *RDR* value is determined as the optimal one in C_i for the given vector tree;

(6) Embed the optimal codeword with the optimal strength $\mathbf{B}_{opt}$, i.e., $\mathbf{T}_w=\mathbf{T}+\mathbf{B}_{opt}*\mathbf{CW}_{opt}^i$.

After all vector trees are embedded with above method, the inverse wavelet transformation is applied to obtain the watermarked image.

Joint coding and embedding Optimization with GA

For a given codeword $\mathbf{CW}$ and vector tree $\mathbf{T}$, the informed embedding process adjusts $\mathbf{T}_w$ to the detectable area of $\mathbf{CW}$ with respect to the LOT detector, which aims to obtain the maximum robustness with minimum distortion. This issue can be formulated as the multi-objective optimization problem, i.e.,

$$\begin{aligned}&\max\ \{z_1=f_R(\mathbf{T},\mathbf{B},\mathbf{CW}),\ z_2=-f_D(\mathbf{T},\mathbf{B},\mathbf{CW})\}\\ &s.t.\ \ z_1\ge R_0\ and\ z_2\le D_0\ ,\end{aligned} \tag{8}$$

where $f_R(\cdot)$ is the robustness measure with respect to LOT, i.e.,

$$\begin{aligned}&f_R(\mathbf{T},\mathbf{B},\mathbf{CW})=L'(\mathbf{T}+\mathbf{B}\cdot\mathbf{CW})_{LOT}\\ &-\max_{j=1}^{N}L'(\mathbf{T}+\mathbf{B}\cdot\mathbf{CW}_j^{'})_{LOT},\mathbf{CW}\in C_i\ ,\mathbf{CW}_j^{'}\notin C_i,\ i=0,1,\end{aligned} \tag{9}$$

and $f_D(\cdot)$ is the measure of distortion, which is preferably defined as the HVS distance between $\mathbf{T}$ and $\mathbf{T}_w=\mathbf{T}+\mathbf{B}\cdot\mathbf{CW}$ considering the imperceptibility constraint. Following the spirit of Watson HVS model in DCT domain [15], the Watson distance in wavelet domain can be defined as follows:

$$D_{\text{wat\_DWT}}(\mathbf{T}_w,\ \mathbf{T})=(\textstyle\sum_{i=1}^{15}\left|\mathbf{B}(i)\cdot\mathbf{CW}(i)/JND(i)\right|^p)^{1/p}\ , \tag{10}$$

where *JND* is the HVS masking value (See [9] for details), and *p* is a constant and generally set to 4.

The multi-objective optimization formulation in (8) can be further simplified as (11), i.e.,

$$\begin{aligned}&\max\quad RDR=f_R(\mathbf{T},\mathbf{B},\mathbf{CW})\ /\ f_D(\mathbf{T},\mathbf{B},\mathbf{CW})\\ &s.\ t.\quad z_1=f_R(\mathbf{T},\mathbf{B},\mathbf{CW})\ge R_0\ and\ z_2=f_D(\mathbf{T},\mathbf{B},\mathbf{CW})\le D_0\ .\end{aligned} \tag{11}$$

The GA (Genetic Algorithm) is then employed to find a joint coding and embedding optimization for the proposed informed watermarking algorithm.

Watermark detection

For each constructed vector tree (refer to Fig.1), the LOT value is calculated for every codeword in C_0 and C_1, among which the one with max LOT is taken as the detected codeword. And the corresponding coset index (0 or 1) is treated as the extracted message bit.

5. EXPERIMENTAL RESULTS

In our simulation, we test five 256*256*8b standard images with different texture, namely, Baboon, Barb, F16, Goldhill, Lena. The images are decomposed with biorthogonal 9/7 wavelet into the 3-level pyramid, among which the coarsest 2-level (scale=2 and 3) are used to construct vector trees. A 1024-bit random sequence is embedded with the related parameters set *N*=32 (coset size) and $D_0=3\cdot15^{1/4}=5.904$. Fig. 3 shows the watermarked images.

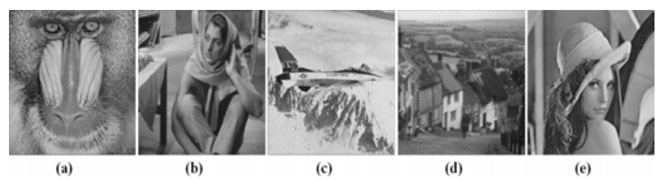

Fig.3 Watermarked image: (a) Baboon (PSNR=35.98dB, $D_{\text{wat\_DWT}}$ = 33.65); (b) Barb (PSNR=41.04dB, $D_{\text{wat\_DWT}}$ =38.42); (c) F16 (PSNR=33.84dB, $D_{\text{wat\_DWT}}$ =29.30); (d) Goldhill (PSNR=36.62dB, $D_{\text{wat\_DWT}}$ =33.67); (e) Lena (PSNR= 36.88dB, $D_{\text{wat\_DWT}}$ =32.77)

To evaluate the feasibility of the proposed watermarking algorithm, we compare the performance of the proposed algorithm with the one in [9], which is also HMM based and among the state-of-the-art robust watermarking algorithm. For convenience, they are named as informed and non-informed watermarking algorithm, respectively. Out of impartiality, the same watermark message of 1024 bits is embedded into the images with each tree inserted with 1 bit, and the same $D_{\text{wat\_DWT}}$ is set. Table I gives the BER performance comparison without attack, which demonstrates that the proposed algorithm achieves significant performance gains over the one in [9] under the same $D_{\text{wat\_DWT}}$ constraint.

Moreover, the watermarked images in Fig.3 are attacked with JPEG compression by StirMark 4.0 [13]. Fig.4 gives the performance comparison between informed and non-informed watermarking algorithm against JPEG compression for image Lena, where significant performance gains are also observed.

The value-metric or gain attack means altering the amplitude of the cover, i.e., $I'(x,y)=\beta*I(x,y),\beta\in R^+$, which is a main weakness of lattice-based dirty paper coding [2]. The images in Fig.3 are attacked with β varying from 0.1 to 2, and the result of watermark detection for Lena is given in Fig.5, where considerable performance improvements with the proposed informed watermarking algorithm is achieved. The informed watermarking algorithm with other test images also has the similar results.

Low-pass filtering attack is also tested with the informed watermarking algorithm and the non-informed one for test image Lena and the low-pass Gaussian filter of width σ_g varying from 0.1 to 1 is used. Fig.6 shows that the proposed informed watermarking algorithm has significant performance gains over the non-informed one in [9].

6. CONCLUSION

In this paper, we present a new informed image watermarking algorithm, which can achieve the information rate of 1/64 bits/pixel with high robustness. The HMM based LOT detector is developed to tackle the issue that the exact embedding strength is unavailable to the receiver when informed embedding strategy is employed. The LOT is then used to design the rules for dirty-paper code construction. The genetic algorithm (GA) is employed for joint coding and embedding optimization to trade-off the robustness and distortion constraints simultaneously. Simulation results demonstrate that the proposed algorithm can achieve high watermarking capacity with high robustness against JPEG, Gaussian noise, gain attack and etc.

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Table I The BER of watermark detection without attack

Algorithm \ Image	Baboon	Barb	F16	Goldhill	Lena
non-informed	0.255	0.181	0.150	0.183	0.136
informed	0.0	0.0	0.0	0.0	0.0

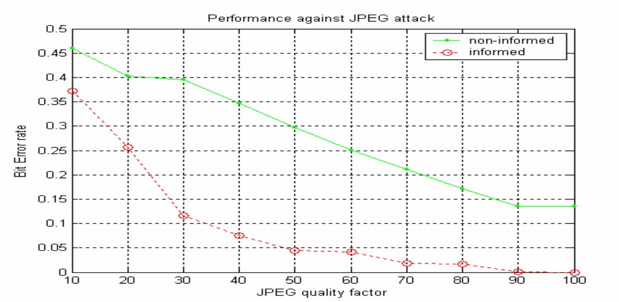

Fig.4 Performance comparison with informed and non-informed watermarking algorithm against JPEG compression for image "Lena"

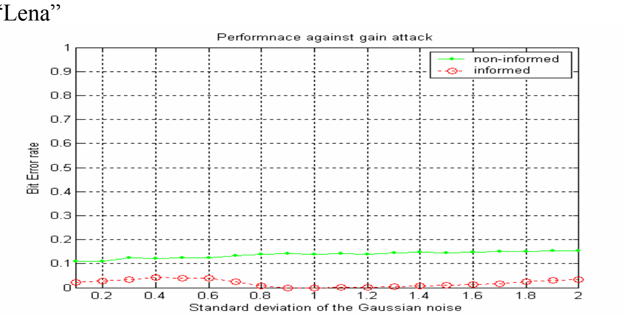

Fig. 5 Performance comparison with informed and non-informed watermarking algorithm against gain attacks for image "Lena"

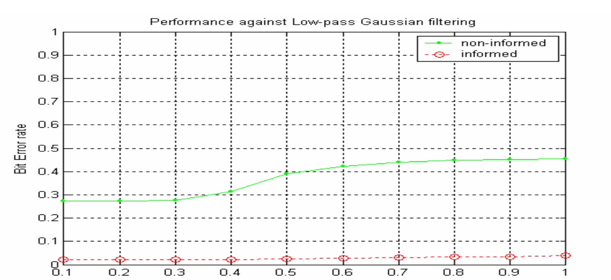

Fig.6 Performance comparison with informed and non-informed watermarking algorithm against low-pass Gaussian filtering for image "Lena"