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An Approach Using Hidden Markov Model to Design A Robust Watermarking Scheme

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Abstract: *This project proposes a new data-hiding method based on Hidden Markov Model. The basic idea of Hidden Markov Model is to use the values of pixel pair as a reference coordinate, and search a coordinate in the neighbourhood set of this pixel pair according to a given message digit. The pixel pair is then replaced by the searched coordinate to conceal the digit. The proposed method offers lower distortion by providing more compact neighbourhood sets and allowing embedded digits in any notational system. The process of informed embedding is formulated as an optimization problem under the robustness and distortion constraints and the genetic algorithm (GA) is then employed to solve this problem. By the existing method we have to perform Image Embedding in secure and effective manner. To avoid artifacts in effective manner we have to apply Adaptive Histogram Equalization as proposed method.*

Index Terms: *Adaptive Histogram Equalization, Hidden Markov Model, Genetic Algorithm.*

I. Introduction

In modern day's image trafficking across the network,security is a big concern which can be achieved bysteganography. Steganography is the art of secretecommunication. The steganography algorithms embed the secret information into different type of natural cover datalike sound and images. The resulting altered data must beperceptually indistinguishable from its natural coverreferred to as stego-data. The goal of steganography is to hide the message/image in the source image by some keytechniques as the result observer has no knowledge of theexistence of the message/image and it is unlikecryptography where the goal is to secure communicationsfrom an eavesdropper by making the data undetectable.As applications of steganography, the hidden data may besecrete message or secrete hologram whose merepresence within the host data set should be non-understandable.For image authentication andidentification data hiding in the image has become animportant technique. The major task for research institute, scientist, and military people is ownership verificationand authentication. A technique for inserting informationinto an image for identification and authentication isknown as image authentication. To protect digital imagedocument from unauthorized access informationsecurity and image authentication has become veryimportant. To hide a message/image inside an imagewithout changing its visible properties the source image may be altered. Developeda useful method for making such alteration by masking,filtering and transformations of the least significant bit(LSB) on the source image

One of the most important topics in digital watermarking community is robust watermarking, which aims at achieving robustness, imperceptibility and high capacity simultaneously. These three objectives, however, are contradictory to each other, and thus a good design is required to achieve an appropriate trade-off between them. Digital watermarking systems are closely related to the problem of communication with side information at the encoder. The pioneer investigation by Costa shows that, only **Z** when the state **S** is known to the encoder. This result motivates the development of robust and high-capacity watermarking systems by considering the watermark as **X** and the host signal as **S** in the Costa's model.

The realization of this idea leads to an informed watermarking technique, which sheds much insight on the design of robust and high capacity watermarking systems and thus becomes a domain of extensive research. Literature shows from the theoretic and practical point of views that informed watermarking can achieve the best performance in robustness and capacity by adapting to the interference introduced by host signals. The informed watermarking schemes in the literatures can be divided into two categories, namely, the quantization index modulation (QIM) proposed by Chen and Wornell and the spread spectrum (SS)-based informed watermarking schemes. The QIM takes the lattice code as the codebook and uses the quantization to perform embedding and decoding. In, Erez and Zamir proved that lattice code can achieve the capacity oflog (l + SNR**)/2** for AWGN channel when the code length approaches infinity. This category of schemes can achieve relatively high capacity with low computational complexity while being generally vulnerable to amplitude scaling attack. Recently, several approaches utilizing the inserted pilot signal and exploiting the rational dither modulation have been developed to improve the robustness against scaling attack.

By adapting to the host, as the source of interference, ISS achieves significant improvement in terms of robustness performance. Two related schemes were proposed, which use informed coding and informed embedding. In informed coding, the message is firstly associated with a coset containing more than one code words, and the optimal code word is then chosen from the associated coset to represent the message, where the correlation detector is usually adopted. In informed embedding, the chosen code word is tailored, according to both the host signal and the constraints of robustness and distortion, so as to put the watermarked signal into the detection region of the chosen code word.

The performance of this HMM-based detector is expected to degrade considerably. To tackle this issue, a new HMM-based Taylor series approximated locally optimum test (TLOT) detector based on the theory of locally optimum test (LOT) and Taylor series approximation is developed to improve the detection performance. Since the strength of the vectors

Ao/Ai is limited in order to achieve imperceptibility, the resulting code words {AooMo} and {Ai oMi} are located in the neighbourhood of Mo and Mi, respectively, which can be efficiently extracted by the TLOT detector. The performance of this TLOT detector is studied and is used to define the robustness metric for determining the optimal embedding strength vectors. In the proposed HMM-based informed watermarking scheme, the process of informed embedding, i.e., the determination of the optimal embedding strength vector is formulated as an optimization problem.

It minimizes the perceptual distortion introduced while achieving a desired level of robustness expressed in terms of the performance of the TLOT detector. The genetic algorithm (GA) with powerful global searching capability is employed to solve the optimization problem and hence determine the embedding strength. Experimental results show that the proposed scheme achieves high robustness against JPEG, AWGN, scaling attack, and low-pass Gaussian filtering (LPGF) with a comparable performance to the state-of-the-art SS-based informed watermarking system, while requiring a significantly reduced arithmetic complexity. This is due to the use of adaptive embedding strength vector which greatly reduces the length of the code words.

II. System Design

Digital watermarking is the act of hiding a message related to a digital signal (i.e. an image, song, and video) within the signal itself. It is a concept closely related to steganography, in that they both hide a message inside a digital signal. However, what separates them is their goal. Watermarking tries to hide a message related to the actual content of the digital signal, while in steganography the digital signal has no relation to the message, and it is merely used as a cover to hide its existence. Watermarking has been around for several centuries, in the form of watermarks found initially in plain paper and subsequently in paper bills. However, the field of digital watermarking was only developed during the last 15 years and it is now being used for many different applications.

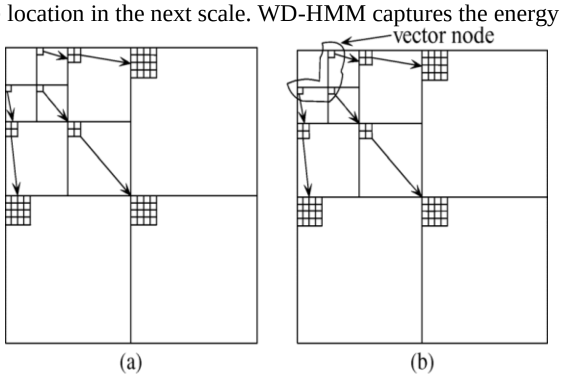
Digital watermarks may be used to verify the authenticity or integrity of the carrier signal or to show the identity of its owners. It is prominently used for tracing copyright infringements and for banknote authentication. Like traditional watermarks, digital watermarks are only perceptible under certain conditions, i.e. after using some algorithm, and imperceptible anytime else. If a digital watermark distorts the carrier signal in a way that it becomes perceivable, it is of no use. Traditional Watermarks may be applied to visible media (like images or video), whereas in digital watermarking, the signal may be audio, pictures, video, texts or 3D models. A signal may carry several different watermarks at the same time. Unlike metadata that is added to the carrier signal, a digital watermark does not change the size of the carrier signal.The needed properties of a digital watermark depend on the use case in which it is applied. For marking media files with copyright information, a digital watermark has to be rather robust against modifications that can be applied to the carrier signal. Instead, if integrity has to be ensured, a fragile watermark would be applied.

1. HMMin wavelet domain

The hidden Markov model in the wavelet domain (WD-HMM) to characterize the behaviour of wavelet coefficients. In WD-HMM, each wavelet coefficient $tj_t k$ has its hidden stateSj k, where j (l < j< J) is the scale and k denotes the fcth wavelet coefficient, where J is the number of scales. Note that j = 1 represents the coarsest scale in our scheme. If there are M hidden statesSj k = m (m = 1... M), each with a state probability $ps_{i,k}$ ($Sj_t k$ =m)

$$= p_{j,k}^{(m)}. \text{ then } \sum_{m=1}^{M} p_{j,k}^{(m)} = 1. \quad f_j(t_{j,k}) = p_j^{(1)} g\left(t_{j,k};\sigma_j^{(1)}\right) + p_j^{(2)} g\left(t_{j,k};\sigma_j^{(2)}\right) \quad (1)$$

where: $p_j^{(1)} + p_j^{(2)} = 1$, $(\sigma_j^{(1)})^2$ and $(\sigma_j^{(2)})^2$ are respective variances of the two Gaussians, and $g(t;\sigma) = \exp(-t^2/2\sigma^2)/\sqrt{2\pi\sigma^2}$ .Consider the wavelet tree in Fig. 1(a) where one parent node (i.e., wavelet coefficient) is linked to its four child nodes at the same location in the next scale. WD-HMM captures the energy dependency across scale by



,**Fig.1. Illustration of WD-HMM and quad tree of wavelet coefficients (three levels). (a) Scalar. (b) Vector.**

Using a Markov chain to describe the probability of hidden state transition from the parent node to its four child nodes as

$$\mathbf{H}_j = \begin{pmatrix} p_j^{1\to1} & p_j^{1\to2} \\ p_j^{2\to1} & p_j^{2\to2} \end{pmatrix}, \quad j = 2,3,\ldots,J \quad (2)$$

wherep^lp-^^{n} represents the probability that the child node is in state n (**n** = 1,2) given that its parent node is in state **m (m =** 1, 2). Thus, the state probability of child node can be determined by,

$$p_j^{(n)} = \sum_{m=1}^{2} p_{j-1}^{(m)} p_j^{m \to n}, \quad j = 2, 3, \ldots, J.$$
(3)

Denote pj = (p^ p^p), where t stands for the matrix transposition, and then we have
P**j** =Pj-i^{H}j = • • • • = **P**iH$_2$H$_3$ • • • Hj, **j** = 2,3,..., J. (4)

The Markov chain links the parent and child nodes together and forms a quad-tree structure of wavelet coefficients, as shown in Fig. 1(a). Thus, WD-HMM for a quad tree can be defined by the following set of parameters:

$$\mathbf{\Theta} = \left\{ \mathbf{p}_1, \mathbf{H}_2, \ldots, \mathbf{H}_J; \sigma_j^{(m)}, (j = 1, \ldots, J; m = 1, 2) \right\}$$
(5)

Since all wavelet coefficients in the same scale are assumed to have same hidden states, the wavelet coefficients of an image can also be characterized.

The WD-HMM model efficiently describes the non-Gaussian behaviour of wavelet coefficients and captures the statistical dependency of wavelet coefficients across scale. This model, however, ignores the existing cross-correlation among the sub band coefficients in different orientations at the same scale. To further enhance the accuracy of WD-HMM in capturing the dependency of wavelet coefficients, Ni et al. proposed a vector WD-HMM (VWD-HMM) and applied it to the design of a new watermarking scheme. In contrast to VWD-HMM, the WD-HMM is named the scalar WD-HMM (SWD-HMM).

In VWD-HMM, the coefficients at the same scale j and location fc at different sub bands are grouped into one vector node as shown in Fig. 4.1(b), which is denoted as $\mathbf{t}_{j,k} = (t_{j,k}^1\ t_{j,k}^2\ t_{j,k}^3)^\tau$, where $t_{j,k}^1, t_{j,k}^2$ and $t_{j,k}^3$ denote the wavelet coefficients at horizontal (H), vertical (V), and diagonal (D) orientations, respectively. Assuming again a Gaussian mixture model of two components with zero mean and co variances $\mathbf{C}_j^{(1)}$ and $\mathbf{C}_j^{(2)}$, the pdf of $\mathbf{t}_{j,k}$ is modelled as

$$f_j(\mathbf{t}_{j,k}) = p_j^{(1)} g\left(\mathbf{t}_{j,k}; \mathbf{C}_j^{(1)}\right) + p_j^{(2)} g\left(\mathbf{t}_{j,k}; \mathbf{C}_j^{(2)}\right)$$
(6)

where g(t\ **C)** denotes the zero-mean multivariate Gaussian density with covariance matrix $\mathbf{C} = E[\mathbf{t}\mathbf{t}^\tau]$

$$g(\mathbf{t}; \mathbf{C}) = \frac{\exp\left(-\frac{1}{2}\mathbf{t}^\tau \mathbf{C}^{-1}\mathbf{t}\right)}{\sqrt{(2\pi)^3 \left|\det(\mathbf{C})\right|}}$$
(7)

Wheredet(C) denotes the determinant of matrix **C** stands for the absolute value. The state transition matrix for VWD-HMM is similar to (2) except that the parent and child nodes are used with their corresponding vector versions. Thus, VWD-HMM for wavelet coefficients of an image is modelled with the following parameter set:

$$\mathbf{\Theta} = \left\{ \mathbf{p}_1, \mathbf{H}_2, \ldots, \mathbf{H}_J; \mathbf{C}_j^{(m)}, (j = 1, \ldots, J; m = 1, 2) \right\}$$
(8)

In the interest of robustness, the coarsest two levels of J-level **(J >= 3)** wavelet pyramid are generally exploited in practice for watermark embedding. Therefore, wavelet coefficients of each image can be simplified as follows:

$$\mathbf{\Theta} = \left\{ \mathbf{p}_1, \mathbf{H}_2; \mathbf{C}_j^{(m)} (j = 1, 2; m = 1, 2) \right\}.$$
(9)

According to, the parameter set $\mathbf{\Theta}$ of SWD-HMM in can be estimated with the expectation-maximization (EM) algorithm that efficiently fits wavelet coefficients of one image to the SWD-HMM. Since VWD-HMM merely replaces the scalar nodes in SWD-HMM with the corresponding vector versions, VWD-HMM can also be estimated with the EM algorithm by simply substituting the scalar variables in with the corresponding vector ones.

2. HMM-Based TLOT Detector
HMM-Based Detector:

The coarsest two-level wavelet pyramid is used for watermarking in the framework of VWD-HMM, which is depicted in Fig. 2 as two-level vector quad-trees. Each two-level vector tree, called **T**, contains five sub vectors or vector nodes, tfc 6 R^3, k = 1,..., 5, which contain, respectively, the three wavelet coefficients labelled by "fc" in the wavelet tree in Fig. 4.2. Hence, **T** has 15 nodes totally and is a vector of 15 dimensions. The 15-node vector tree will serve as the basic unit for watermarking in our scheme. Particularly, it is used as the carrier for the watermark message, where a code word depending on a binary message bit is added. The message will be extracted using the HMM-based detector. According to (6), the pdf of each tfc can be expressed as,

$$f_t(\mathbf{t}_k) = p_j^{(1)} g\left(\mathbf{t}_k; \mathbf{C}_j^{(1)}\right) + p_j^{(2)} g\left(\mathbf{t}_k; \mathbf{C}_j^{(2)}\right) (j = 1\ for\ k = 1;\ j = 2 \text{ otherwise}).$$
(10)

In the framework of VWD-HMM, the vector nodes at the same scale are statistically independent and the child vector nodes are statistically dependent via the Markov chain on their parent vector nodes.

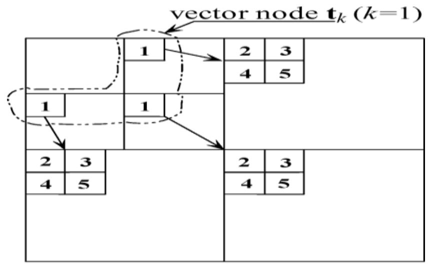


Fig. 2. Illustration of coarsest two-level wavelet pyramid for watermarking, where coefficients with the same number are grouped into one vector node $\mathbf{t}_k$.

$q_{\mathbf{t}}(\mathbf{t}_k|\mathbf{t}_1)\ (k = 2,\ldots,5)$ be the pdf of t1 and the pdf of tk conditioned on t1, respectively, and then they can be represented in terms of $f_t(\mathbf{t}_k)$ as follows:

$$\begin{cases} q_{\mathrm{t}}(\mathbf{t}_1) = f_{\mathrm{t}}(t_1) = \mathbf{p}_1^{\tau}\mathbf{g}_{1,1} \\ q_{\mathrm{t}}(\mathbf{t}_k|\mathbf{t}_1) = f_{\mathrm{t}}(\mathbf{t}_k) \\ \qquad = p^{(1)}(\mathbf{t}_k|\mathbf{t}_1)\cdot g\left(\mathbf{t}_k; \mathrm{C}_2^{(1)}\right) \\ \qquad\quad + p^{(2)}(\mathbf{t}_k|\mathbf{t}_1)\cdot g\left(\mathbf{t}_k; \mathrm{C}_2^{(2)}\right) \\ \qquad = \mathbf{p}^{\tau}(\mathbf{t}_k|\mathbf{t}_1)\mathbf{g}_{2,k} = (\mathbf{p}_1\mathbf{H}_2)^{\tau}\mathbf{g}_{2,k} \end{cases} \tag{11}$$

where $p^{(m)}(t_k|t1)$ (m = 1, 2; k = 2,...,5) denotes the probability of the hidden state S2 = m of t_k when the parent vector node ti is given, $\mathbf{p}(t_k|t1) = (p^{(1)}(t_k|t1), p^{(2)}(t_k|t1))^r$ (k = 2,...,5) and $\mathbf{g}_{j,k} \triangleq (g(\mathbf{t}_k C_j^{(1)}), g(\mathbf{t}_k; C_j^{(2)}))^{\tau}$ (j = 1,2; k = **1,**..., 5). The joint pdf of **T** is thus given by

$$f_{\mathrm{T}}(\mathrm{T}|\Theta) = q_{\mathrm{t}}(\mathrm{t}_1)\cdot\prod_{k=2}^{5} q_{\mathrm{t}}(\mathrm{t}_k|\mathrm{t}_1) = \prod_{k=1}^{5} f_{\mathrm{t}}(\mathrm{t}_k). \tag{12}$$

Suppose that n message bits are to be embedded in a particular vector tree **T** and it is associated with one of the 2^n initial code words $\mathbf{M}_l \in \{\mathbf{M}_1,\ldots,\mathbf{M}_{2^n}\}$ each of which is a 15-D vector. Then, this 15-D code word $\mathbf{M}_l$, is embedded into **T** to generate the watermarked vector tree $\mathbf{Y}$ as $\mathbf{Y} = \mathbf{T} + \mathbf{A}_l \circ \mathbf{M}_l$, where "o" denotes the element-wise product and $\mathbf{A}_l$ is a 15-D embedding strength vector. For blind informed watermarking, $\mathbf{A}_l$ is determined in encoder and unavailable to the detector.

$$\begin{aligned} f_{\mathbf{T}}(\mathbf{Y}|\mathbf{A}_l\circ\mathbf{M}_l,\boldsymbol{\Theta}) &= f_{\mathbf{T}}(\mathbf{Y}-\mathbf{A}_l\circ\mathbf{M}_l|\boldsymbol{\Theta}) \\ &= \prod_{k=1}^{5} f_{\mathbf{t}}(\mathbf{y}_k - \boldsymbol{\alpha}_{lk}\circ\mathbf{m}_{lk}) \end{aligned} \tag{13}$$

where $\mathbf{y}_k = \mathbf{t}_k + \boldsymbol{\alpha}_{lk}\circ\mathbf{m}_{lk}$, $\boldsymbol{\alpha}_{lk}$ and $\mathbf{m}_{lk}$ are the three-element sub embedding strength vector of A; and the sub code of M; corresponding to the A;th sub vector tfc, respectively. Note that the embedding ruleis used to simplify the design of the detector. To recover the message from **Y**, we apply the theory of hypothesis testing. Firstly, we define the likelihood ratio as

$$\begin{aligned} L_{\mathbf{A}_l}(\mathbf{Y}) \triangleq L(\mathbf{Y}|\mathbf{A}_l\circ\mathbf{M}_l) &= \frac{f_{\mathbf{T}}(\mathbf{Y}|\mathbf{A}_l\circ\mathbf{M}_l,\boldsymbol{\Theta})}{f_{\mathbf{T}}(\mathbf{Y}|\boldsymbol{\Theta})} \\ &= \frac{f_{\mathbf{T}}(\mathbf{Y}-\mathbf{A}_l\circ\mathbf{M}_l|\boldsymbol{\Theta})}{f_{\mathbf{T}}(\mathbf{Y}|\boldsymbol{\Theta})} = \prod_{k=1}^{5}\frac{f_{\mathrm{t}}(\mathbf{y}_k-\boldsymbol{\alpha}_{lk}\circ\mathbf{m}_{lk})}{f_{\mathrm{t}}(\mathbf{y}_k)}. \end{aligned} \tag{14}$$

By using the maximum likelihood criterion, we then obtain the optimal detected codeword as follows:

$$\mathrm{M}_{\mathrm{opt}} = \arg\max_{l=1,\ldots,2^n} L_{\mathbf{A}_l}(\mathbf{Y}) = \arg\max_{l=1,\ldots,2^n} L(\mathbf{Y}|\mathbf{A}_l\circ\mathbf{M}_l). \tag{15}$$

The detector is named the vector HMM (VHMM) detector for convenience. In the proposed informed watermarking scheme, only one message bit (n = 1) will be embedded in each vector tree to achieve good robustness performance.

TLOT Detector:

The exact embedding strength vector Ai is unavailable at the blind informed watermarking detector. Consequently, the performance of the watermark detector may degrade considerably. To cope with this issue, we apply the locally optimum hypothesis testing method and derive the HMM-based TLOT detector. Since the derivation of LOT detector is rather technical, the details are presented in Appendix A and we simply give the results as follows,

$$\mathrm{M}_{\mathrm{opt}} = \arg\max_{l=1,2,\ldots,2^n} L_{\mathrm{A}_l}(\mathrm{Y})_{\mathrm{LOT}} = \arg\max_{l=1,2,\ldots,2^n} \sum_{k=1}^{5}\left(-\frac{f_t'(\mathrm{y}_k)}{f_t(\mathrm{y}_k)}\cdot \mathrm{m}_{lk}\right) \quad (16)$$

where $f_t'(\mathbf{y}_k)$ is the derivative of $f_t(\mathbf{y}_k)$ with respect to $\mathbf{y}_k$, which is given by

$$f_t'(\mathrm{y}_k) = p_j^{(1)} g\left(\mathrm{y}_k; \mathrm{C}_j^{(1)}\right)\left(-\mathrm{y}_k^{\tau}\left(\mathrm{C}_j^{(1)}\right)^{-1}\right) + p_j^{(2)} g\left(\mathrm{y}_k; \mathrm{C}_j^{(2)}\right)\left(-\mathrm{y}_k^{\tau}\left(\mathrm{C}_j^{(2)}\right)^{-1}\right) = \begin{cases} \mathrm{p}_1^{\tau}\mathrm{u}_{1,1}\mathrm{g}_{1,1}, & j=1, k=1 \\ (\mathrm{p}_1\mathrm{H}_2)^{\tau}\mathrm{u}_{2,k}\mathrm{g}_{2,k}, & j=2, k=2,\ldots,5 \end{cases} \quad (17)$$

where $\mathbf{u}_{j,k} \triangleq diag(-\mathbf{y}_k^{\tau}(\mathbf{C}_j^{(1)})^{-1}, -\mathbf{y}_k^{\tau}(\mathbf{C}_j^{(2)})^{-1})$. It is observed from that, with the LOT detector, the strength vector $\mathbf{A}_l$ or α_{lk} is no longer necessary for the detection of $\mathbf{M}_{\mathbf{opt}}$ from **Y.**

The developed HMM-based detector would serve as the robustness metric in the framework of wavelet-based informed embedding which will be addressed in Section VI. It is observed that, even though a sufficiently large embedding strength is put into the host signal to make y change significantly, would not respond correspondingly. To explain the behaviour of the HMM-based LOT detector, we examine the covariance matrix $\mathbf{C} = E[\mathbf{y}\mathbf{y}^{\tau}]$, which is a real symmetric matrix. Since the wavelet coefficients in different orientations at the same scale have weak correlation, the values on the main diagonal of **C,** say σ_1^2, σ_2^2, and σ_3^2, are much larger than the others. Thus, all the principal minor determinants of C will be larger than zero, i.e., C is a positive definite matrix and $(-\mathbf{y}^{\tau}\mathbf{C}^{-1}\mathbf{y}/2)$ is non positive. According to our extensive test using the EM algorithm mentioned in Section II on 100 512-by-512 grey images with different texture characteristics, σ_i^2 (i = 1,2,3) is at least in the order of 10, which is also consistent with the "sharp peak and heavy tails" distribution of wavelet coefficients.

Thus, det(C) that mainly depends on $(\sigma_1^2\sigma_2^2\sigma_3^2)$ would be at least in the order of 10^3 and accordingly $\mathbf{C}^{-1}$ would have small entries at most in the order of inverse of the ten (i.e.) 10^{-1}. Therefore, $g(\mathbf{y};\mathbf{C}) = \exp(-\mathbf{y}^{\tau}\mathbf{C}^{-1}\mathbf{y}/2)/\sqrt{(2\pi)^3|\det(\mathbf{C})|}$ would have a small variation less than $1/\sqrt{8000\pi^3}$ even when the variation of $\mathbf{y}(i)\ (i = 1,2,3)$ due to water mark insertion changes from $-\infty$ to ∞. As a result, the direct use of LOT detector would make the informed embedding process quite difficult to find an optimal direction for optimization. The distortion would thus be increased, which is undesirable.

To alleviate the mentioned problem of the LOT detector, we proceed to approximate g{y; **C)** via Taylor series and propose the Taylor series approximated LOT (TLOT) detector as follows. For the same reason as mentioned previously, the term $(-\mathbf{y}^{\tau}\mathbf{C}^{-1}\mathbf{y}/2)$ takes a value small enough such that g**(y; C)** can be approximated by a Taylor series as

$$g(\mathrm{y};\mathrm{C}) \approx \frac{\left(1 - \frac{1}{2}\mathrm{y}^{\tau}\mathrm{C}^{-1}\mathrm{y} + \frac{1}{8}(\mathrm{y}^{\tau}\mathrm{C}^{-1}\mathrm{y})^2\right)}{\sqrt{(2\pi)^3|\det(\mathrm{C})|}} \triangleq b(\mathrm{y};\mathrm{C} \quad (18)$$

Where $b(\mathrm{y};\mathrm{C}) = (1 - \mathrm{y}^{\tau}\mathrm{C}^{-1}\mathrm{y}/2 + (\mathrm{y}^{\tau}\mathrm{C}^{-1}\mathrm{y})^2/8)\sqrt{(2\pi)^3|\det(\mathrm{C})|}$.

Substituting (18) into (11) yields $h_t(\mathbf{y}_k)$, of $f_t(\mathbf{y}_k)$, i.e.,

$$h_t(\mathbf{t}_k) = \begin{cases} \mathbf{p}_1^\tau \mathbf{b}_{1,1}, & j = 1, k = 1 \\ (\mathbf{p}_1 \mathbf{H}_2)^\tau \mathbf{b}_{2,k}, & j = 2, k = 2, \ldots, 5 \end{cases} \quad (19)$$

Where $\mathbf{b}_{j,k} = (b(\mathbf{y}_k; \mathbf{C}_j^{(1)}); b(\mathbf{y}_k; \mathbf{C}_j^{(2)}))^\tau$ Similarly, $f_t'(\mathbf{y}_k)$ can also be approximated by a Taylor series as

$$h_t'(\mathbf{y}_k) = \begin{cases} \mathbf{p}_1^\tau \mathbf{u}_{1,1} \mathbf{b}_{1,1}, & j = 1, k = 1 \\ (\mathbf{p}_1 \mathbf{H}_2)^\tau \mathbf{u}_{2,k} \mathbf{b}_{2,k}, & j = 2, k = 2, \ldots, 5. \end{cases} \quad (20)$$

By substituting (4.19) and (4.20) into (4.16), we obtain the TLOT detector defined as follows,

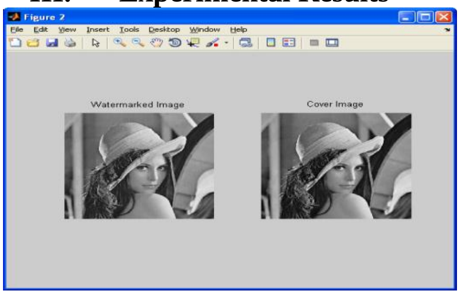
$$\begin{aligned} \mathbf{M}_{\text{opt}} &= \underset{l=1,2,\ldots,2^n}{\arg\max}\ L_{\mathbf{A}_l}(\mathbf{Y})_{TLOT} \\ &= \underset{l=1,2,\ldots,2^n}{\arg\max} \sum_{k=1}^{5} \left(-\frac{h_t'(y_k)}{h_t(y_k)} \cdot \mathbf{m}_{lk} \right). \end{aligned} \quad (21)$$

Adaptive Histogram Equalization:

The AHE process can be understood in different ways. In one perspective the histogram of grey levels (GL's) in a window around each pixel is generated first. The cumulative distribution of GL's, that is the cumulative sum over the histogram, is used to map the input pixel GL's to output GL's. If a pixel has a GL lower than all others in the surrounding window the output ismaximally black; if it has the median value in its window the output is 50% grey. This section proceeds with a concise mathematical description of AHE which can be readily generalized, and then considers the two main types of modification. The relationship between the equations and different (conceptual) perspectives on AHE, such as GL comparison, might not be immediatelyclear, but generalizations can be expressed far more easily in this framework.

By this method, the digital watermarkingis the act of hiding a message related to a digital signal (i.e. an image, song, and video) within the signal itself can be performed better.

III. Experimental Results



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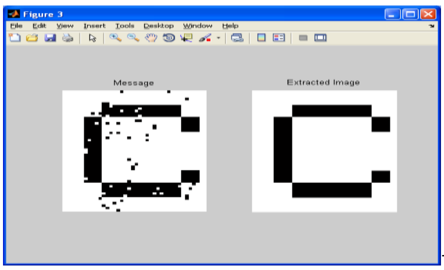

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IV. Conclusion

In this paper, we have presented a new HMM-based informed watermarking algorithm with high robustness and simplified complexity at an information rate of 1/64 bit/pixel. An adaptive histogram equalization is used in this method. The input watermark image undergo equalization technique to improve the contrast of the image. A TLOT detector is developed to address the problem of unavailability of exact embedding strength in the receiver due to informed embedding. It achieves a similar performance to the original HMM-based detector in [20] under the unperceivable fidelity constraint. The TLOT detector is also utilized to develop robustness metric and facilitate the design of dirty-paper code used in our scheme. The perceptual distance in the wavelet domain is constructed to perform perceptual shaping and to measure the fidelity of the watermarked image. Based on the developed robustness metric and the perceptual distance, the process of informed embedding is formulated as an optimization problem under the robustness and distortion constraints. Then GA is employed to solve the optimization problem. Extensive simulations demonstrate that the HMM-based informed watermarking algorithm has high robustness against JPEG, AWGN, scaling attack, and LPGF and has a comparable performance to the state-of-the-art SS-based informed watermarking algorithm in [7] with a significantly reduced complexity.

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References

[1] I. J. Cox, M. L. Miller, and J. A. Bloom, Digital Watermarking. San Mateo, CA: Morgan Kaufmann, 2001.

[2] P. Moulin and R. Kotter, "Data-hiding codes," Proc. IEEE, vol. 93, no. 12, pp. 2083-2016, Dec. 2005.

[3] M. H. M. Costa, "Writing on dirty paper," IEEE Trans. Inform. Theory, vol. IT-29, no. 3, pp. 439-441, May 1983.

[4] I. J. Cox, M. L. Miller, and A. L. McKellips, "Watermarking as communications with side information," Proc. IEEE, vol. 87, no. 7, pp. 1127-1141, Jul. 1999.

[5] B. Chen and G. W. Wornell, "Quantization index modulation methods: A class of provably good methods for digital watermarking and information embedding," IEEE Trans. Inform. Theory, vol. 47, no. 4, pp. 1423-1443, May 2001.

[6] J. J. Eggers, J. K. Su, and B. Girod, "A blind watermarking scheme based on structured codebooks," Proc. Inst. Elec. Eng., Secure Images and Image Authentication, vol. 4, pp. 1-6, Apr. 2000.

[7] M. L. Miller, G. J. Doerr, and I. J. Cox, "Applying informed coding and embedding to design a robust high capacity,watermark," IEEE Trans. imageProcess.,vol.13,no.6,pp.792-807,Jun.2004.

[8] A. Abrardo and M. Barni, "Informed watermarking by means of orthogonal and quasi-orthogonal dirty paper coding," IEEE Trans. Signal Process. vol. 53, no. 2, pp. 824-833, Feb. 2005.

[9] S. Voloshynovskiy, F. Deguillaume, S. Pereira, and T. Pun, "Optimal adaptive diversity watermarking with channel state estimation," in Proc. SPIE Security and Watermarking of Multimedia Contents III, Bellingham, WA, 2011, vol. 4134, pp. 23-27, SPIE Press.

[10] P. Moulin and J. A. O'Sullivan, "Information-theoretic analysis of information hiding," in Proc. IEEE Int. Symp. Inform. Theory, Jun. 2000, p. 19.

[11] P. Moulin, "The role of information theory in watermarking and its application to image watermarking," Signal Process., vol. 81, no. 6, pp. 1121-1139, Jun. 2001.

[12] A. S. Cohen and A. Lapidoth, "The Gaussian watermarking game," IEEE Trans. Inform. Theory, vol. 48, no. 6, pp. 1639-1667, Jun. 2002.

[13] W. Yu, A. Sutivong, D. Julian, T. M. Cover, and M. Chiang, "Writing on colored paper," in Proc. ISIT, Washington, DC, Jun. 24-29, 2001.

[14] P. Moulin and Y. Wang, "Capacity and random-coding exponent for channel coding with side information," IEEE Trans. Inform. Theory, vol. 53, no. 4, pp. 1326-1347, Apr. 2007.

[15] U. Erez and R. Zamir, "Achieving 0.5 over the additive white Gaussian noise channel with lattice encoding and decoding,"IEEE Trans. Inform Theory, vol. 50, no. 10, pp. 2293-2314, Oct. 2004.

[16] J. J. Eggers, R. Bäuml, and B. Girod, "Estimation of amplitude modifications before SCS watermark detection," in Proc. SPIE Security Watermarking Multimedia Cont. IV, Jan. 2002, vol. 4675, pp. 387-398.

[17] F. Perez-Gonzalez, C. Mosquera, M. Barni, and A. Abrardo, "Rational dither modulation: A high-rate data-hiding method invariant to gainattacks," IEEE Trans. Signal Process., vol. 53, no. 10, pp. 3960-3975, Oct. 2005.

[18] H. S. Malvar and A. F. Florencio, "Improved spread spectrum: A new modulation technique for robust watermarking," IEEE Trans. SignalProcess., vol. 51, no. 4, pp. 898-905, Apr. 2003.

[19] M. S. Crouse, R. D. Nowak, and R. G. Baraniuk, "Wavelet-based statistical signal processing using hidden Markov models," IEEE Trans.Signal Process., vol. 46, no. 4, pp. 886-902, Apr. 1998.

[20] J. Ni, R. Zhang, J. Huanga, and C. Wang, "A robust multibit image watermarking algorithm based on HMM in wavelet domain," in Proc.IWDW2005, 2005, pp. 110-123, LNCS 3710.

[21] H. V. Poor, An Introduction to Signal Detection and Estimation. New York: Springer-Verlag, 1994.

[22] G. Mitsuo and R. W. Cheng, Genetic Algorithms and Engineering Design. New York: Wiley, 1997.

[23] C. Wang, J. Ni, R. Zhang, G.-K. Kwon, and S.-J. Ko, "Content-adaptive robust image watermarking with posterior HMM-based decoder,"IEICE Trans. Fundermentals, vol. E91-A, no. 8, Aug. 2008.

[24] A. B. Watson, "DCT quantization matrices optimized for individual images," Human Vision, Visual Processing, and Digital Display IV,vol. SPIE-1913, pp. 202-216, 1993.