PERFORMANCE ANALYSIS OF TEXT HALFTONE MODULATION

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ABSTRACT

This paper analyzes the use of text halftone modulation (THM) as a text hardcopy watermarking method. Using THM, text characters in a document have their luminances modified from the standard black to a gray level generated with a given halftone screen, according to a message to be transmitted. The application of THM has been discussed in [3, 6]. In this paper, a spectral metric is proposed to detect the embedded message. Based on this metric, an error rate analysis of halftone modulation is presented considering the effects of the print and scan channel. Experiments validate the analysis and the applicability of the method.

***Index Terms*—** Watermarking, spectral detection, print-scan.

1. INTRODUCTION

Although telephony, video and Internet based communications have increased remarkably in the last few years, communication over paper is still an essential mean of conveying information. Very often, important paper copies of documents are exchanged between companies and people. As a consequence, the development of a reliable method for authentication of hardcopy documents remains a critical challenge.

As discussed in [3], a possible approach to text document authentication is to consider text as a data structure consisting of several modifiable features such as size, shape, position, luminance, color, etc. These features can be modified, possibly unperceptually to the human eye, according to a side message (or watermark message) to be embedded in the document. Another useful method is to embed information by modifying the characters using different halftone matrices [8] according to the message, as illustrated in Fig. 2. This is referred to as text halftone modulation (THM) in this paper. It was proposed in [3] and [6], where the authors claim that it has a superior performance in comparison to simple text luminance modulation (TLM) [3, 4], illustrated in Fig. 1. In contrast to TLM, where the character average luminance is used to detect a modified character, in THM a spectral analysis of the character is performed to detect the halftone patterns.

Based on the THM method, the contributions of this paper are manifold. (i) To detect the embedded halftone screen, the energy of the sub-bands of the power spectral density (PSD) of a modulated character is used. (ii) The detection error rate using this detection metric is analyzed, considering a print and scan (PS) channel model. (iii) The information of each subband of the received character is combined according to the Bayes classifier [5], to achieve a reduced error rate. (iv) Experiments are provided to illustrate the validity of the analyses and the applicability of the method.

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This paper is organized as follows. Sec. 2 briefly discusses halftoning algorithms and describes a PS model. Sec. 3 outlines the TLM and THM techniques. Sec. 4 proposes a detection metric based on the PSD and analyzes the performance of this metric. To illustrate the validity of the proposed model and the applicability of the method, selected experimental results are presented in Sec. 5. The paper closes with relevant conclusions in Sec. 6.

2. THE PRINT AND SCAN CHANNEL

2.1. The Halftoning Process

This section describes the halftoning process, which occurs prior to printing. This description is focused on ordered dithering halftoning.

Let s be a digital image of size $M \times N$ with $L+1$ levels in the range [0,1], where **0 represents white** and **1 represents black**. A halftoned image (binary) b is generated from s, using the ordered dithering halftoning algorithm. The output of this method depends on the size and on the coefficients of the *dithering matrix* D of size $J \times J$, where each coefficient represents a threshold level and the coefficient values in D are approximately uniformly distributed. Each coefficient takes a value from the set $\{0, 1/L, 2/L, \ldots, 1\}$. The binary output image b is given by an element-by-element thresholding operation between the pixels in s and the coefficients in D. In general, $J \ll M$ and $J \ll N$. The input-output relationship of ordered dithering can be mathematically described by:

$$b(m,n) = \begin{cases} 0 & \text{if} \quad s(m,n) < D(m \bmod J, n \bmod J) \\ 1 & \text{otherwise} \end{cases} \tag{1}$$

where the output '0' represents a white pixel (do not print a dot), and '1' represents a black pixel (print a dot). Clearly, the coefficients in D have a direct effect on the quality of the halftone image. Two common eye-pleasing dither matrices structures are those based on green- and blue-noise halftoning models [8]. Green noise models produce an output formed mostly of midfrequencies spectral components. Blue noise models produce an output formed mostly of high-frequency components. These two kinds of halftoning models are applied in this paper for text watermarking.

2.2. A Print and Scan Channel

Analytical models of the PS channel have been presented in the literature [1, 2, 4]. In addition to the geometric distortions (possible rotation, re-scaling, and cropping), PS models assume that the process can be modeled by low-pass filtering, the addition of Gaussian noise, and non-linear gains, such as brightness and gamma alteration. In the following a modified PS channel model is described, which includes the halftone signal.

The digital scanned image y is represented by

$$y(m,n) = g_s\Big\{\big\{g_{pr}[b(m,n)] + \eta_1(m,n)\big\}* \\ * h_{ps}(m,n)\Big\} + \eta_3(m,n), \quad (2)$$

where b is the halftoned image generated from the original image s, as described in (1). η_1 represents printing noise due to microscopic ink and paper imperfections. The noise η_3 combines illumination and CCD electronic noise [1], as well as the quantization noise due to A/D. The operator $*$ represents convolution and the linear system h_{ps} is a low-pass filter combining the point-spread functions of the printer and of the scanner. In the printing process, blurring occurs due to toner or ink spread. In the scanning process, the low-pass effect is due to the optics and the motion blur caused by the interactions between adjacent CCD arrays elements [1].

The term $g_{pr}(\cdot)$ in (2) represents a gain in the printing process. In practice, when toner or black ink particles are applied over the paper, they do not present a null reflectance, causing a luminance gain to the printed image. This distortion is described by $g_{pr}(m,n) = \alpha(m,n)b(m,n)$, where α is a gain affecting the black elements of b. α is modeled as constant for a small region (an area corresponding to a full character, for example), but it does vary throughout a full page due to non-constant printer toner distribution.

The term $g_s(\cdot)$ represents the response of scanners, which vary depending on the device. They may cause a non-linear gain to the scanned image, represented by $g_s(m,n) = [x(m,n)]^{\phi}$ as reported in results presented in [1].

3. DESCRIPTION OF TLM AND THM

Using TLM and THM, each character in the original digital document is labeled as c_i, $i = 1, 2, \ldots, K$, where K is the total number of elements. The elements are labeled from left to right, and from top to bottom.

In TLM, information is embedded by individually altering the luminance of c_i through an embedding function where each character has its luminance modulated from black to any value in the real-valued discrete alphabet $\Omega = \{\omega_1, \omega_2, \ldots, \omega_S\}$ of cardinality S, so that each symbol conveys $\log_2 S$ bits of information. Considering a spatial coordinate system for each character, indexed by coordinates (m,n), $c_i(m,n)$ is modulated by a gain w_i, $w_i \in \Omega$. Assume that $c_i(m,n) \in \{0,1\}$ and $w_i \in [0,1]$, the modified luminance pixels are in the range $[0,1]$, from white (level 0) to black (level 1). The general embedding function is given by:

$$s_i(m,n) = w_i c_i(m,n) \quad (3)$$

where s_i is the output element. The process is illustrated in Fig. 1 for $S = 2$, with a very high gain.

Fig. 1: Example of text watermarking through TLM.

In contrast to TLM, THM modifies the characters with specific halftone matrices, as illustrated in Fig. 2.

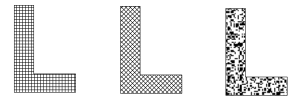


Fig. 2: Exaggerate illustration of different halftone patterns.

4. SPECTRAL DETECTION

4.1. Statistical and Distortion Assumptions

Using TLM, text characters have their luminances modified to convey information. The printed version of the modified characters can be halftoned with different matrices D. Characters of equivalent luminances printed using different D's present the same average luminance after printing, however the spectral characteristics are significantly different.

In the model in (2), it is possible to decompose b into a constant term $\bar{b}$ plus a noise term η_2, such that $b(n) = \bar{b} + \eta_2(n)$. Different dithering matrices D cause different spectral characteristics to the noise η_2. Dither matrices coefficients can be set [9] to output a pattern with blue-noise or green-noise [8] characteristics, for example. In order to detect spectral differences, assume that $\eta_2 = \eta_b * h_D$ where η_b is a white-noise pattern and h_D represents a filter with the frequency characteristics of the desired halftone.

Due to the low perceptual impact requirement of watermarking, the detector operates in a small range of the luminance range $[0,1]$. For this reason, g_s in (2) can be approximated to a linear model [1] and ϕ in g_s is approximated to 1 for simplicity. Assuming that b is generated from a constant gray level region, that is, $s(n) = s_0 = \bar{b}$, where s_0 is the average luminance of the modulated character prior to printing, (2) can be written as (using a one-dimension notation)

$$y(n) = \big\{\alpha[s_0 + \eta_2(n)] + \eta_1(n)\big\} * h_{ps}(n) + \eta_3(n), \quad (4)$$

The term α represents a gain (see g_{pr} in (2)) that varies slightly throughout a full page due to non-uniform printer toner distribution. Due to its slow rate of change, α is modeled as constant in n but it varies with each realization i satisfying $\alpha \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2)$, where i represents the $i-$th character in TLM watermarking.

Due to the nature of the noise (discussed in Section 2) and based on experimental observations, η_1 and η_3 can be generally modeled as zero-mean mutually independent Gaussian noise [1, 2].

4.2. Proposed Spectral Detection Metric

With the assumptions above, a possible detection metric to classify a given character is to use sub-band spectral features. For this task, the PSD of a scanned character $y(n)$ of size N is divided into L subbands of size W, where $W = N/L$. The average power of each of these subbands represents one among L features.

Let the average power of l-th sub-band be given by

$$d_l = \frac{1}{W} \sum_{w=W(l-1)}^{lW-1} |Y(w)|^2 \quad (5)$$

where $|Y_i(w)|^2 = Y_i(w)Y_i^{\ast}(w)$ represents the squared PSD of $y(n)$, where the operator $\ast$ denotes complex conjugate and $Y(w)$

is

$$Y(w) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} y(n) e^{-j2\pi nw/N} = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} \Big\{ \{\alpha[s_0 + \eta_2(n)] + \eta_1(n)\} * h_{ps}(n) + \eta_3(n) \Big\} e^{-j2\pi nw/N} \tag{6}$$

To determine to which class the received vector $y(n)$ belongs, the average power of each sub-band l is used as a feature. Therefore, the feature classification vector is given by $\mathbf{d} = [d_1 \ d_2 \ \ldots \ d_L]^T$.

The expected value μ_{d_l} of a feature d_l is given by:

$$\begin{aligned} \mu_{d_l} &= E\{d_l\} = E\Big\{ \frac{1}{W} \sum_{w=W(l-1)}^{lW-1} |Y(w)|^2 \Big\} \\ &= E\Big\{ \frac{1}{W} \sum_{w=W(l-1)}^{lW-1} \frac{1}{(N^2)} \sum_{n=0}^{N-1} \{\alpha s_0 * h_{ps}(n) + \alpha\eta_2(n) * h_{ps}(n) \\ &\quad + \eta_1(n) * h_{ps}(n) + \eta_3(n)\} e^{-j2\pi nw/N} \sum_{m=0}^{N-1} \{\alpha s_0 * h_{ps}(n) \\ &\quad + \alpha\eta_2(n) * h_{ps}(n) + \eta_1(n) * h_{ps}(n) + \eta_3(n)\} e^{j2\pi nw/N} \Big\} \end{aligned} \tag{7}$$

Considering the statistical characteristics (zero-mean, mutually independent) assumed for the noise terms in (4), the cross terms are canceled and the expected value in (7) becomes

$$\begin{aligned} \mu_{d_l} = \frac{1}{W} \sum_{w=W(l-1)}^{lW-1} & \alpha^2 s_0^2 H_{ps}(w) H_{ps}^*(w) \delta(w)/N \\ & + \alpha^2 H_{ps}(w) H_{ps}^*(w) \sigma_{\eta_2}^2 + H_{ps}(w) H_{ps}^*(w) \sigma_{\eta_1}^2 + \sigma_{\eta_3}^2 \end{aligned} \tag{8}$$

where $\delta(\cdot)$ is the unit impulse function. Similarly, a statistical analysis shows that, when N is large, the variance $\sigma_{d_l}^2 = E\{d_l^2\} - \mu_{d_l}^2$ of a feature d_l can be approximated to:

$$\begin{aligned} \sigma_{d_l}^2 = \frac{1}{W^2} \sum_{w=W(l-1)}^{lW-1} \sum_{v=W(l-1)}^{lW-1} & 3\sigma_{\eta_2}^4 (3\sigma_\alpha^4 + 6\sigma_\alpha^2 \mu_\alpha^2 + \mu_\alpha^4) \\ & |H_{ps}(w)|^2 |H_{ps}(v)|^2 + 3\sigma_{\eta_1}^4 (\sigma_\alpha^2 + \mu_\alpha^2) |H_{ps}(w)|^2 |H_{ps}(v)|^2 \\ & + 3\sigma_{\eta_3}^4 - \mu_{d_l}^2 \end{aligned} \tag{9}$$

Assuming that d_l is normally distributed, from μ_{d_l} and $\sigma_{d_l}^2$ the theoretical detection error rates are determined, presented in Sec. 5.3.

4.3. Combining Metrics

To reduce the detection error rate, all the sub-band features d_l ($l = 1, \ldots, L$) are combined. For this, the Bayes classifier [5] is used because of its optimality properties for normally distributed features, which is the case assumed. Moreover, it is possible to combine other detection metrics (spectral or statistical), with the spectral metric proposed in this paper. Although different metrics may have better performance than others, because both the spectral and the statistical metrics are useful to separate classes, combining them increases the distance between classes, and consequently reduces the detection error rate [5], at the expense of increasing computational complexity.

5. EXPERIMENTS

The purpose of this section is to illustrate through Monte Carlo simulations the applicability of THM and the reduced error rate when using the Bayes classifier, as well as to validate the analyses of Section 4 and the proposed PS channel model. In addition, comparative results with TLM are presented.

During the experiments, the noise and the distortion parameters of the PS channel vary depending on the printing and scanning devices used. The printing and scanning resolutions were set to 300 dots/inch and pixels/inch, respectively. The experiments are conducted with printers HP IJ-855C, HP IJ-870Cxi and HP LJ-1100, and scanners Genius HR6X, HP 2300C and HP SJ-5P. Typical values for the parameters in (2) are $\sigma_{\eta_1} = 0.018$, $\sigma_{\eta_3} = 0.01$, $\mu_\alpha = 0.8$, $\sigma_\alpha = 3$.

To model the low-pass effect of the PS channel represented by h_{ps} in (2), the filter described in [4] is used in this paper, which is a Butterworth filter of order 1 and cut-off frequency equal to 0.17. Using the noise, gain and blurring filter parameters described above, a character distorted with the proposed PS model is perceptually similar to an actual printed and scanned character.

5.1. Experiment 1: Blue Noise Halftoning

Consider the 1 bit/element case ($S = 2$). A large sequence of $K = 32520$ characters (as in 'abcdef...') is printed, with font type 'Arial', size 13 points. In the experiments small text elements such as commas and dots are not watermarked. Because these elements are composed by a smaller number of pixels, they are more susceptible to segmentation and detection errors.

Prior to printing, the character sequence was modulated with a gain $w_i = 1$ (no luminance alteration) for odd i, $i = 1, 3, \ldots, K-1$, and with a gain $w_i = 0.84$ for even i, $i = 2, 4, \ldots, K$, using a blue noise dithering matrix D. Using these values, empirical tests indicate that it is hard for a human observer to distinguish between a modulated and a non-modulated character.

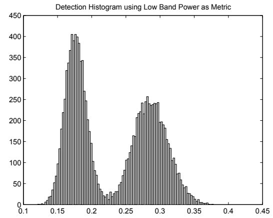
The elements with no luminance alteration ($w_i = 1$) have white-noise characteristics and carry bit 0, and the elements modulated with $w_i = 0.84$ have blue noise characteristics and carry bit 1. The task is to classify each printed character as having a bit 0 or bit 1 embedded into it.

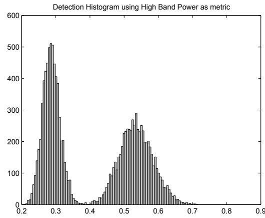
To retrieve the embedded information, the document is scanned and the text is segmented from the background using simple thresholding.Segmentation errors are not observed in this set of tests, however it is clear that they may cause synchronization detection errors. The use of channel coding is an efficient option to reduce the bit errors caused by wrong segmentation [7].

To determine the bit value inserted in each element of the scanned document, three distinct approaches are tested:

1. **Detection using one sub-band feature:** The resulting detection distributions using the low and the high bands energies separately as detection metrics are given in Figs. 3(a) and 3(b) respectively.
2. **Detection using two sub-band features:** The resulting detection distribution combining the low and the high bands energies with the Bayes classifier is given in Fig. 3(c).
3. **Detection using three sub-band features:** The resulting detection distribution combining the low, the mid and the high bands energies with the Bayes classifier is given in Fig. 3(d)

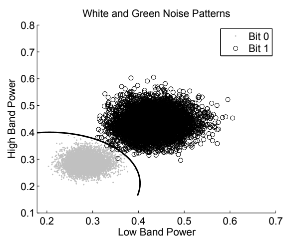
Table 1 presents the observed error rates for the three cases discussed above. Notice the reduced error rate when more metrics are

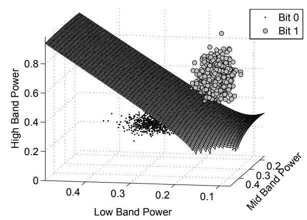




(a) Histogram of the low-band as a detection metric.

(b) Histogram of the high-band as a detection metric.





(c) Scattered plot illustrating the low and high bands for blue noise.

(d) 3-D plot illustrating the low, middle and high bands.

Fig. 3: Detection distributions using one, two and three metrics.

Table 1: Experimental error rates for THM and TLM.

Freq. Band	**Blue Noise**	**Green Noise**
Low	9.66×10^{-3}	1.03×10^{-2}
High	4.66×10^{-3}	7.48×10^{-3}
Comb. Low-High	1.12×10^{-3}	2.14×10^{-3}
Comb. Low-Mid-High	7.80×10^{-4}	9.96×10^{-4}
Average Lum.(TLM)	1.05×10^{-2}	1.07×10^{-2}

included in the detection process. This table also presents the error rates using only the average luminance as a detection metric (TLM), which presents a higher error rate than the spectral detection.

5.2. Experiment 2: Green Noise Halftoning

This experiment is similar to Experiment 1, however green noise halftoning is employed in the printing process. Table 1 presents the observed error rates. Notice that blue noise presents a smaller error rate in comparison to green noise. This occurs because when blue noise (with strong high frequencies) and green noise (with strong mid frequencies) are passed through the PS channel, blue noise is more distinguishable from white noise, which corresponds to the non-modulated case.

5.3. Experiment 3

In this experiment a Monte Carlo simulation is performed to observe the error rates when using the proposed PS channel model of Section 2. The goal of this experiment is to validate the analyses of Section 4 for the synthetic PS channel, which emulates the actual PS process. Therefore, in this experiment, instead of printing and scanning the modulated symbols, they are transmitted through the assumed model. Tests are performed with blue and green noise halftoning, for $w_i = 0.98$, 0.96, 0.92, 0.88, and 0.84, $i = 2, 4, \ldots, K$. In this experiment, $K = 500000$.

The curves in Fig. 4 represent the theoretical error rates plotted from the results of Sec. 4 for blue and green noise halftoning, as

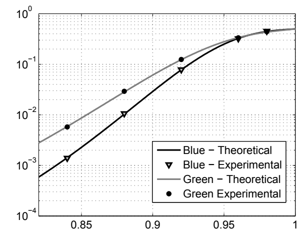


Fig. 4: Error probability for different gains, using blue and green noise halftoning to modulate the characters.

indicated by the legend. The triangles and the black dots represent the observed experimental error rates, presenting an excellent correspondence to the theoretical curves. This validates the analyses of Sec. 4 and illustrates that once the noise parameters of PS devices are obtained, the performance of the system can be predicted.

6. CONCLUSIONS

This paper proposes and analyzes a new detection approach to THM, a text hardcopy watermarking method. Blue and green noise halftoning patterns are employed in the printing process to modify text characters and consequently embed a watermark in a document. The proposed detection observes the spectral characteristics of the received character. Considering a PS channel, the theoretical detection error rates are determined, and the experimental results illustrate a good correspondence between theory and practice. The experiments and the analyses have illustrated that THM presents a smaller error rate than TLM, making it a practical alternative for document authentication. It is important to notice that it is possible to combine THM with other text watermarking methods [3].

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