A Novel Least Distortion Linear Gain Model for Halftone Image Watermarking Incorporating Perceptual Quality Metrics

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Abstract. In this paper, a least distortion approach is proposed for halftone image watermarking. The impacts of distortion and tonality problems in halftoning are analyzed. An iterative linear gain model is developed to optimize perceptual quality of watermarking halftone images with efficient computation complexity $O(1)$. An optimum linear gain for data hiding error diffusion is derived and mapped into a standard linear gain model, with the tonality evaluated using the average power spectral density. As compared with Fu and Au's data hiding error diffusion method, our experiments show that our proposed linear gain model can achieve an improvement of between 6.5% to 12% using weighted signal-to-noise ratio (WSNR) and an improvement of between 11% to 23% measured by visual image fidelity (VIF).

1 Introduction

Halftoning is an important operation that transforms conventional grayscale and color images into bi-level images that are particularly useful for print-and-scan processes [1]. In fact many images and documents displayed in newsprint and facsimile are halftone images. The problems of copyrights protection and unauthorized tampering of digital content, particularly in printed and scanned form, are becoming increasingly widespread that need to be addressed. As such, digital watermarking [2] can be very useful in protecting printable halftone images for business, legal and law enforcement applications. In the recent literature, researchers have proposed a variety of approaches to data hiding and watermarking but many were designed for multi-tone images and could not be applied for halftone image directly.

In general, halftone watermarking approaches are classified as (1) error diffusion-based halftone watermarking. a watermark is embedded into a halftone image during an error diffusion process. In [3], Fu and Au proposed this approach. The main idea is that performing self-toggling in N pseudo random locations, the error of self-toggling plus the error of standard error diffusion halftoning diffuse to neighboring pixels. A private key is required in the verifier

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side to generate N pseudo random locations to be used for retrieving the watermark. In [4], Sherry and Savakis proposed data hiding cell parity (DHCP) and data hiding mask toggling (DHMT) based on Fu and Au's approach to improve the halftone perceptual quality. However, the image quality was affected due to the frequency distortion arises by error diffusion process itself. In this paper, the quality preserving solution has been studied to compensate the distortion issue while watermarking embedding; (2) data hiding in multi-halftone images in order to increase capacity. A watermark was embedded into two or more halftoning images, revealing the watermark when these embedded images were overlaid [5]. In [6], the watermark was decoded using a look up table (LUT). The above methods have the disadvantage that the extracted watermark contains residual patterns from the two overlaid images, thus reduces the fidelity of the extracted watermark image. In [5], an iterative isotropic algorithm and coordinate projection were proposed to solve the problem described above. However, the contrast of the embedded images was found to be lower than using other methods. (3) watermarking in dither halftoning. Watermarking in dither halftone images is proposed in [7][8]. The advantage of dither halftone watermarking is low complexity but the image quality will be degraded. Besides, the embedded capacity is non-flexible. In [9], high quality progressive coding was proposed to embed a watermark into a dithered halftone image but the quality was found to be lower than Fu and Au's method [3]. (4) watermarking in Direct Binary Search (DBS) halftoning. In [10], Kacker and Allebach proposed a framework to address the feasibility of a joint halftoning and watermarking scheme for a grayscale image. The block-based spread spectrum watermarking scheme was applied to a grayscale image, along with a DBS halftoning algorithm. A HVS-based error metric was used to analyze the watermarked halftone image. This joint method was found to provide better quality based on the watermark correlation criterion. However, the computational requirements increased for some applications, which could be a potential drawback.

Halftone quality and robustness are the two main challenges for watermarking halftone images. The robustness of watermarking can be enhanced by incorporating error correction coding [11]. However, data hiding error diffusion is not trivial since embedding data into halftone image downgrades the perceptual quality of halftone image. It is difficult to increase robustness without causing a significant amount of perceptual distortion because error correction coding requires high capacity of watermarks to be embedded into halftone image.

In this paper, we analyze the sharpening distortion in data hiding error diffusion and propose a watermarking linear gain model to address how to compensate perceptual quality via minimizing distortion in data hiding error diffusion of halftone images. In error diffusion halftoning, a grayscale image is quantized into one bit pixel via an *error diffusion kernel* [1][12]. As a consequence, it sharpens the image and adds quantization noise resulting in artifacts and idle tones. However, some artifacts and idle tones are incurred even without watermark embedding. The main aim of our proposed method is to preserve the least distortion data hiding error diffusion in halftone images.

Furthermore, we propose the use of average power spectrum $\overline{PSD}$ to measure harmonic distortion of halftone and embedded halftone images, analogous to total harmonic distortion (THD) [13]. Experiments show that the proposed iterative halftone watermarking model not only optimizes the perceptual quality of watermarking halftone images but also reduces tonality, with overall perceptual quality significantly better than Fu and Au's method tested on similar images.

The rest of the paper is organized as follows. In Section 2, related work is reviewed. In Section 3, we describe a watermarking embedding process and how the distortion can be modeled and eliminated via an iterative linear gain model. In Section 4, an iterative linear gain halftoning embedding is designed and implemented. In Section 5, we perform experiments to compare perceptual image quality of our proposed method to that of Fu and Au's approach. also the tonality problem is analyzed. We conclude and discuss future work in Section 6.

2 Related Work

Halftoning quantizes a grayscale or color image into one bit per pixel. There are mainly three existing methods [1], i.e., error diffusion, dithering and iterative methods (DBS). Most error diffusion halftones use *an error diffusion kernel* to minimize local weighted errors introduced by quantization. The error caused by quantizing a pixel into bi-levels is diffused into the next-processing neighbour pixels, according to the weights of the diffusion kernel. The two popular error diffusion kernels are those of Jarvis [14] and Floyd and Steinberg [15]. Most error filters have coefficients that sum to one, which guarantee that the entire system would be stable.

Most of the embedding methods use standard error diffusion frameworks. Fu and Au's embedding approach [3] divides an image into macro blocks and one bit of watermark is embedded into each block. A halftone pixel is changed to an opposite value $1 \rightarrow 0$ or $0 \rightarrow 1$, if the embedded watermark is **0** or **1** which is opposite to the image value. The watermark can be retrieved simply by extracting embedding locations in the halftone image. This approach is relatively straightforward. However, as the embedding bits increase in each block, the same value pixels may cause cluster, i.e., regionally white pixels(**1**) or black pixels(**0**) together. The cluster downgrades the overall image quality. Pei et al. [6] proposed a least-mean-square data hiding halftoning where the watermark was embedded into two or more halftone images by minimal-error bit searching and a LUT was used to retrieve the watermark. The goal of their approach is to increase watermark capacity rather than image quality. Wu [5] proposed a mathematical framework to optimize watermark embedding to multiple halftone images where the watermark image and host images were regarded as input vectors. The watermark were then extracted by performing binary logical operation i.e., XOR) to multiple halftone images. Guo et al. [9] proposed high quality progressive coding for watermarking dithered halftone image. Their method did not provide better image quality than Fu and Au's method.

In this paper we propose a method which takes into account the effects of watermarking embedding on the error diffusion halftoning process. Our goal is to build a mathematic analysis to answer why the watermarking in error diffusion process impacts the image quality and how to compensate it to preserve image perceptual quality.

3 Analysis of Halftoning Distortion in Data Hiding Error Diffusion

In this section, we analyze the key effects of sharpening and noise during the watermarking embedding process of halftone images. Idle tones also will be discussed in Section 5.1

3.1 Sharpening Problems in Data Hiding Error Diffusion

Knox [16] analyzed the quantization error in halftoning at each pixel, which is correlated with the input image. He found that the quantization error was the key reason causing annoying artifacts and *worms* in halftoning. Although worms can be reduced, the sharpness of halftone increases as the correlation of the error image with the input image increases. Sharpening distortion affects perceptual quality of the halftone image [12]. On the other hand, toggling halftone pixels in data hiding error diffusion may increase the quantization errors. Thus, the perceptual quality of image cannot be preserved.

To better model a halftone quantizer, Kite et al. [12] introduced a linear gain plus additive noise model, and applied it to error diffusion quantizer. We summarize his model as follows.

Let $x(i,j)$ is the grayscale image input and $e(i,j)$ is the quantization error caused by the quantizer output $Q(*)$ minus the quantizer input $x'(i,j)$. H(z) is the error diffusion kernel which diffuses the quantization error into neighbor pixels. A standard error diffusion can be expressed as

$$e(i,j) = y_0(i,j) - x'(i,j) \tag{1}$$

$$x'(i,j) = x(i,j) - h(i,j) * e(i,j) \tag{2}$$

$$y_0(i,j) = Q(x'(i,j)) \tag{3}$$

A quantizer output $y_0(i,j) = Q(x'(i,j))$ can be modeled as

$$Q(x'(i,j) = K_s x'(i,j) + n(i,j) \tag{4}$$

where K_s is a linearization constant based on the uncorrelated white noise $n(i,j)$ assumption. The value of K_s at any pixel is given by the ratio of the output of the quantizer to its input. Because the input to the quantizer may vary over a finite range, the output is binary, K_s varies with the input [12]. The K_s can be predicted by minimizing the square error between the halftone and model output shown in Equation (5). Based on Kite et al.'s theoretical analysis [12], $K_s \in [1, \infty]$.The visual quality of halftone image will be preserved if $K_s x'(i,j)$ is approaching halftone output infinitely, i.e., minimizing the squared error between halftone and halftone linear gain model outputs as a criterion:

$$\min_{K_s}\sum_{i,j}(K_s x'(i,j) - y(i,j))^2 \tag{5}$$

Equations (4) and (5) will be true under the circumstance of the uncorrelated white noise assumption of residual image.

In data hiding error diffusion halftoning, we adapt Kite et al. [12] error diffusion process and combine it with watermarking embedding. We begin by specifying K_w as a linear gain in Figure 1 (K_s represents a linear gain for standard halftone [12]) and proposed a multiplicative parameter L_w compensating input image during data hiding error diffusion process as follows

$$e(i,j) = y(i,j) - x'(i,j) \tag{6}$$
$$x'(i,j) = x(i,j) - h(i,j) * e(i,j) \tag{7}$$
$$x''(i,j) = x'(i,j) + L_w x(i,j) \tag{8}$$
$$y_0(i,j) = Q(x''(i,j)) \tag{9}$$
$$y(i,j) = R(y_0(i,j)) \tag{10}$$

where $R(*)$ in the Equation (10) represents the watermarking self-toggle quantizer. We substitute $K_w x'(i,j)$ into quantizer output $y(i,j)$ as a data hiding

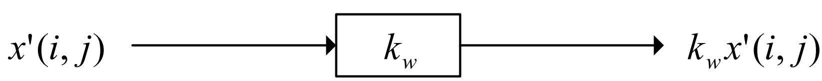


Fig. 1. Data hiding error diffusion linear gain model

error diffusion linear gain model. By adjusting a multiplicative parameter L_w, the signal linear gain model output $K_w x'(i,j)$ would approach to watermarked halftone output infinitely, i.e., minimizing the criterion (5) with K_s replaced by K_w. However, K_w can not be estimated by the criterion (5) as long as a watermarked halftone $y(i,j)$ is obtained. But we can map K_w to standard halftone linear gain K_s in Section 3.2.

Now we use Lena image and Jarvis kernel error diffusion as examples to illustrate how L_w could be useful to reduce the correlation between the residual error image and input image(original). The correlation can be quantified as correlation coefficient [17].

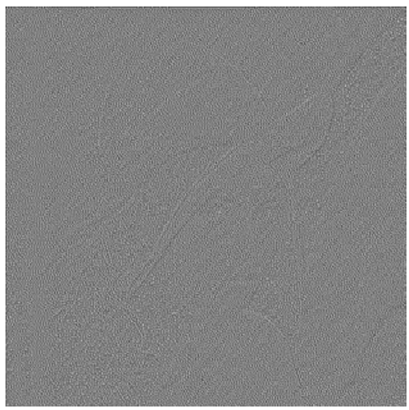
$$C_{EI} = \frac{|COV[EI]|}{\sigma_E \sigma_I} \tag{11}$$

Where σ_E and σ_I are the standard deviation of residual image E and input image I, and COV[EI] is the covariance matrix between them. The residual error images (halftone - original) for Fu and Au method and our proposed method are analyzed in Figure 2.

(a) Lena image

(b) Our proposed watermarked Lena image with 10080 bits embedded, K_w=2.0771

(c) Fu and Au's method residual error image,corr=0.0238



(d) Our proposed method's residual error image,corr=0.0110,K_w=2.0771

Fig. 2. Watermarked Halftone and Residual Error Images

Both Fu and Au's method and our proposed method embedded a binary image logo. In our case, the University of Surrey logo (90*112) [18] was used. Figure 2(a) is original Lena image. Figure 2(b) is watermarked halftone lena image based on our proposed method. Figure 2(c) is the residual error image (embedded halftone - original) based on Fu and Au's method. This residual image shows the correlation between the residual image with the input image (corr=0.0238) during data hiding error diffusion. Figure 2(d) represents our residual image based on our embedding model. From the above figures, we observe in our proposed method the residual image is approximately representing the noise (corr=0.0110). This correlation is significantly reduced as compared to Fu and Au's method. Thus, according to our experiments the sharpness of a watermarked halftone image decreases as the correlation reduces.

3.2 Determine K_w for Data Hiding Error Diffusion

In this section, we derive the mapping from K_w to K_s. Here K_s can be estimated from a standard error diffusion kernel [12]. We consider the embedding of watermark into a block-based halftoning process based on Fu and Au's method. The watermark embedding locations are determined via a Gaussian random variable. As a result, the watermark sequences become white noise embedded into the halftone image. However, due to self-toggling, the watermark bit $w(i,j)$ (0 or 1) can change the pixels in the original halftone image at the selected embedding locations of standard halftone output $y_0(i,j)$(1 or 0) in the host image. We have developed two cases for the embedding procedure.

Case 1: Embedded bit $w(i,j) = y_0(i,j)$. Let a linear gain K_w represents data hiding error diffusion linear gain. The best case scenario is that all watermark bits equal to the standard halftone output $y_0(i,j)$. In this case, none of pixel $y_0(i,j)$ will be toggled. We can simplify by taking $K_w = K_s$ corresponding with $L_w = L_s$ to reduce the sharpening of original halftone.

Case 2: Embedded bit $w(i,j) \neq y_0(i,j)$. The worst case scenario is that all standard halftone outputs $y_0(i,j)$ have to be changed. In this case, the watermarked halftone output $y(i,j)$ becomes $1 - y_0(i,j)$. Our watermarked error diffusion process is described in Equation (6) to Equation (10).

We can simply Equation (10) as follow:

$$y(i,j) = 1 - y_0(i,j) \tag{12}$$

By taking z-transformation to Equations (6-10), we obtain the Equation (13)(the detailed derivation of Equations see Appendix).

$$L_w = \frac{1 - K_w}{K_w} \tag{13}$$

Equation (13) establishes the mapping from K_w to L_w.

Now we derive the linear gain K_w for data hiding error diffusion mapped to K_s. Using the watermarking linear gain $K_w x'(i,j)$ to reach the watermarked halftone output $y(i,j)$, this can be realized by minimizing the squared error between watermarked halftone and linear gain model output as indicated in Equation (14).

$$\min_{K_w} \sum_{i,j} (K_w x'(i,j) - y(i,j))^2 \tag{14}$$

In data hiding error diffusion, the criterion (5) can be approximated with an infinite small real number $\delta_1 \geq 0$ for the watermarking linear gain model:

$$|K_w x'(i,j) - y(i,j)| = \delta_1 \tag{15}$$

By relaxing the absolute value of Equation (15) (we know watermarked halftone $y(i,j) \in [0,1]$) , we obtain

$$K_w x'(i,j) = y(i,j) + \delta_1 \tag{16}$$

Recall in case 1, in order to minimize (5) for standard halftone linear gain K_s, we derive (17) with a small real number $\delta_2 \geq 0$

$$K_s x'(i,j) - y_0(i,j) = \delta_2 \tag{17}$$

Recall in case 2, replace $y(i,j)$ in Equation (5) with (12), and a small real value $\delta_3 \geq 0$, and relax absolute value, we obtain

$$K_s x'(i,j) + y_0(i,j) = 1 + \delta_3 \tag{18}$$

Combine (17) and (18), we obtain

$$2K_s x'(i,j) = 1 + \delta_2 + \delta_3 \tag{19}$$

From (16) and (19), for halftone image $|y(i,j)| \leq 1$, we obtain

$$\frac{K_w x'(i,j)}{2K_s x'(i,j)} = \frac{y(i,j) + \delta_1}{1 + \delta_2 + \delta_3} \leq 1 \tag{20}$$

Therefore, we derive $K_w \leq 2K_s$. The watermarked halftone linear gain can be represented by $K_w \in [K_s, 2K_s]$. As we mentioned K_w cannot be obtained without a watermark embedded. Each watermark embedded in the halftone image has a unique K_w value that can minimize the criterion $\sum_{i,j}(K_w x'(i,j) - y(i,j))^2$. This minimization is achieved by our proposed iterative linear gain model as described in section 4.

4 Iterative Linear Gain for Watermarking Error Diffusion

In Section 3, we analyzed sharpening distortion in data hiding error diffusion. In this section, we propose our visual quality preserving algorithm for data hiding error diffusion via iterative linear gain for watermarking halftone. By adjusting a multiplicative parameter L_w to compensate the input image in data hiding halftoning, the sharpening distortion decreases as the correlation between original image and residual image decreases. Thus, we can obtain the least distortion watermarked halftone image. This results in our proposed iterative linear gain model for optimum perceptual image quality of halftone images as illustrated in Figure 3.

4.1 Iterative Data Hiding Error Diffusion Algorithm

We found that the greater linear gain K_w the lesser the sharpening and harmonic distortion. To accurately measure a perceptual quality of a halftone image, Kite et al. [12] proposed the use of weighted SNR (WSNR) for the subjective quality measure of halftone image. WSNR weights the Signal-to-Noise Ratio (SNR) according to the contrast sensitivity function (CSF) of the human visual system. For an image of size $M \times N$ pixels, WSNR is defined as

$$WSNR(dB) = 10 \log_{10}\left(\frac{\sum_{u,v} |(X(u,v)C(u,v)|^2}{\sum_{u,v} |(X(u,v) - Y(u,v)C(u,v)|^2}\right) \tag{21}$$

where $X(u,v), Y(u,v)$, and $C(u,v)$ represent the Discrete Fourier Transforms (DFT's) of the input image, output image, and CSF, respectively, and $0 \leq u \leq M-1$ and $0 \leq v \leq N-1$. With WSNR, we optimize K_w to minimize the halftone watermarking image distortion. In Section 3, as the K_w increases, the correlation between residual error image and input image is reduced. We use an iterative approach to find the best K_w for maximum WSNR of embedded halftone image. In this way, we can find the least distortion halftone watermarking image. Based on this concept, our new halftone embedding process is illustrated in Figure 3. The embedding process first divides an image into macro blocks. Each macro block embeds one bit. Toggling halftone pixels is the same as Fu and Au's method [3] so that if the bit of watermark is the same as the original halftone pixel, no action is taken. If the watermark bit is different from the halftone pixel, then the bit is toggled.

However, K_w can only be determined if a watermark is embedded, which is a random combination between 0 and 1. Thus, in Section 4 we inferred our estimation of K_w from the Case one and Case two based on the estimation of K_s. We concluded $K_w \in [K_s, 2K_s]$. In our algorithm, K_w is selected by starting from K_s, and the algorithm iterates by adding one additive amount b, i.e., $b = 0.2$ to K_w in each loop. It generates corresponding halftone image measured by WSNR. We measured K_w empirically using five test images and results are shown in Figure 4. It is found as the K_w varies the WSNR increases until it peakes at the point. Our K_w starts from K_s and increased by step of 0.2. The K_w varies within $[K_s, 2K_s]$. The corresponding WSNR is computed. Once the maximum WSNR value is found, the iteration will then terminates.

The calculation of WSNR is shown in Equation (21), where $X(u,v)$ is the input image shown as the numerator, $Y(u,v)$ is output image, $X(u,v) - Y(u,v)$ shown as the denominator which presents the noise image. The maximum WSNR will be found when the denominator in Equation (21) is infinitely small. It is similar to the process of minimizing the quantization noise (the differential between output and input) shown in Equation (14). However, the quantization noise will never be zero or equivalent to white noise. Otherwise the denominator in Equation (14) will be

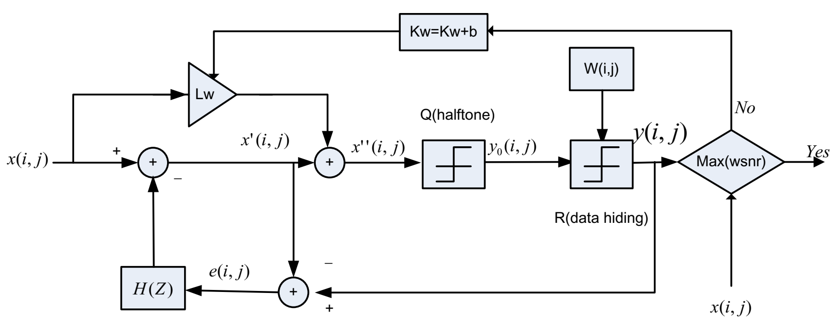


Fig. 3. Iterative linear gain halftone embedding

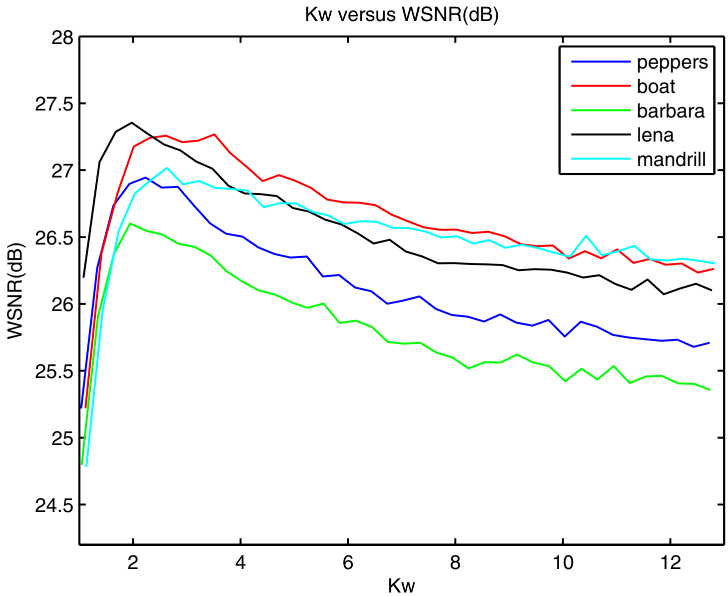


Fig. 4. The relationship between K_w and WSNR

Table 1. Iteration numbers

loop step	peppers	boat	barbara	lena	mandrill
0.2	8	8	7	6	9
0.3	6	7	5	5	7

equal to zero. We simulated the WSNR variation with an increase of K_w presented in Figure 4. Each image in Figure 4 has a peak value of WSNR corresponding to a unique K_w which minimizes the criterion indicated in Equation (14). As noticed, for boat image, there is another peak value after the first. It is because the Equation (14) is an approximated value. Its quantization noise may be not pure white noise. This exceptional value doesn't affect the algorithm to find the best possible quality of image.

The mathematics proof of explicit relationship between $K_w(K_s)$ and WSNR can not be provided at this stage. But it would be interesting to explore in the future.

The complexity of our iterative algorithm is $O(1)$ because our algorithm will terminate once the first maximum WSNR has been found in the iteration. The maximum point defines as the current WSNR greater than the next value of WSNR. In our theoretical analysis, the K_w value is estimated as $[K_s, 2K_s]$. Even when the iterative step is very small, the iteration number will be limited when the maximum WSNR is found subject to the Equation 14. The iteration number for each test image has been recorded and presented in Table 1.

5 Experiments and Results Analysis

Modified Peak Signal-to-Noise Ratio (MPSNR) [3] and Weighted Signal-to-noise Ratio(WSNR) [12] have been commonly used for evaluating halftone image quality. However, one main disadvantage of MPSNR is that it only compares the original image with the watermarked halftone image. The watermarked halftone image first undergos a Gaussian low-pass filter while the original image still contains high frequency components. This results in the inaccurate calculation of SNR because errors are incurred due to high frequency components remained in the grayscale image.

Our experiments were performed on five images with different sizes of watermark embedded using The University of Surrey logo in Jarvis kernel. Each experiment uses the same embedding locations and different watermark sizes. Figure 2(b) is lena halftone image with 10080 bits (90*112) embedded at K_w=2.077 with WSNR=27.37 (dB). We use WSNR metric for subjective quality comparison of watermarked halftone quality as given in Table 2 and MPSNR in Table 3. From Table 2, our approach has an average improvement of 6.5% over Fu and Au's method. MPSNR measure shows that our approach is slightly higher than Fu and Au's method except for the image mandrill and barbara in high capacity embedding. This may be caused by the fact that both mandrill and barbara contained some high frequency components.

Figure 5 illustrates the results of applying our proposed method and Fu and Au's method data hiding error diffusion to five test images. From this figure, we conclude our approach can preserve the high quality of watermarked halftone with different sizes of watermark embedded. Overall Fu and Au's method cannot maintain the WSNR as good as our method for different host images. This is due

Table 2. WSNR Comparison Between Our's Method and Fu and Au's Method (dB)

mark size	32x32		64x64		90x90		90x112		Avg. Impr.%
image	our	Fu & Au	our	Fu & Au	our	Fu & Au	our	Fu & Au	our impr.
peppers	27.643	25.273	27.380	25.164	27.073	25.098	26.936	25.068	8.392
boat	27.582	24.674	27.533	24.673	27.231	24.609	27.112	24.570	11.470
barbara	27.224	24.923	27.133	24.825	26.778	24.669	26.558	24.585	8.734
lena	27.729	26.038	27.618	25.920	27.449	25.868	27.375	25.830	6.565
mandrill	27.222	24.116	27.066	24.094	26.972	24.076	26.909	24.005	12.474

Table 3. MPSNR Comparison Between Our's Method and Fu and Au's Method (dB)

mark size	32x32		64x64		90x90		90x112	
image	our	Fu and Au	our	Fu and Au	our	Fu and Au	our	Fu and Au
peppers	27.168	26.729	26.958	26.567	26.705	26.429	26.601	26.327
boat	26.048	25.710	25.965	25.651	25.733	25.455	25.598	25.404
barbara	24.095	24.078	23.998	23.997	23.844	23.856	23.772	23.785
lena	27.017	26.917	26.895	26.783	26.701	26.653	26.623	26.560
mandrill	22.620	22.724	22.581	22.670	22.505	22.620	22.463	22.572

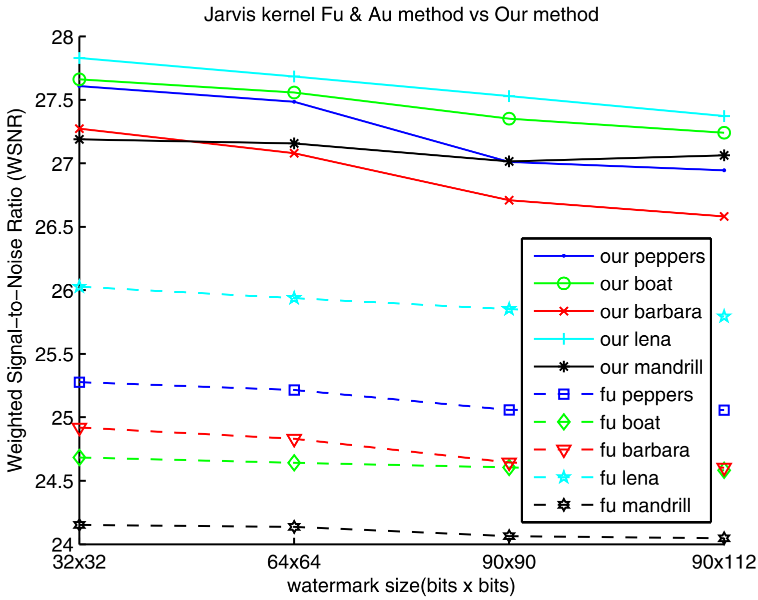


Fig. 5. WSNR of Fu method vs Our method

to our iterative linear gain model can effectively compensate the watermarking effects during halftone error diffusion process.

Figure 6 illustrates the percentage of improvement of our method over Fu and Au's method. Even for the worst case image *lena*, our method achieved an improvement of approximately 6-7% compared to Fu and Au's method. The other watermarked halftone images are shown in Figure 9.

Furthermore, the latest visual quality evaluation called *visual information fidelity (VIF)* [19] was proposed to use human visual system (HVS) model for image quality assessment (QA). VIF is a model for distortion (22) and can be used to quantify the loss of image information to the distortion process and explore the relationship between image information and visual quality. We use it to compare the loss of image distortion between different watermarking halftone images. Table 4 are measured results for both Fu and An's method and our method. These results show that our model have $11\% - 23\%$ improvement than Fu and Au's method. This confirms the effectiveness of our iterative linear gain model in data hiding error diffusion so as to achieve the least distortion image.

$$VIF = \frac{\sum(subbands\ of\ wavelet\ coefficients\ in\ distorted\ image)}{\sum(subbands\ of\ wavelet\ coefficients\ in\ reference\ image)} \tag{22}$$

5.1 Tonality Validation in Watermarked Halftone Image

Idle tones appears as strong cycle patterns. Idle tones affect the quality of halftone. Kite et.al [12] analogized the halftone distortion, which was caused

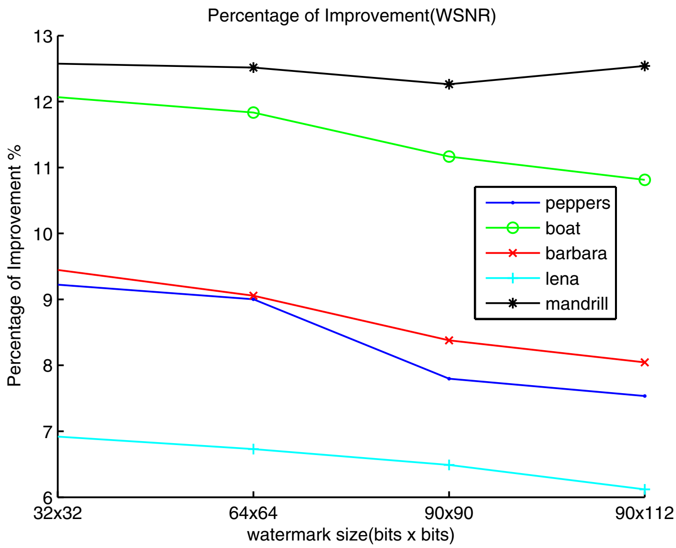


Fig. 6. Percentage of improvement of our method

Table 4. VIF Comparison Between Our's Method and Fu and Au's Method

mark size	32x32		64x64		90x90		90x112		VIF comp.		
image	our	Fu	our	Fu	our	Fu	our	Fu	our avg.	Fu avg.	Impr. (%)
peppers	0.2519	0.2165	0.2551	0.2125	0.2413	0.2066	0.2405	0.2075	0.2472	0.2108	17.2753
boat	0.2534	0.2004	0.2467	0.1995	0.2407	0.1968	0.2380	0.1959	0.2447	0.1981	23.5004
barbara	0.2494	0.2208	0.2411	0.2175	0.2336	0.2105	0.2306	0.2083	0.2387	0.2143	11.3768
lena	0.2456	0.2108	0.2425	0.2092	0.2418	0.2044	0.2345	0.2043	0.2411	0.2072	16.3821
mandrill	0.2242	0.1882	0.2250	0.1866	0.2227	0.1845	0.2201	0.1838	0.2230	0.1858	20.0365

by idle tone, with total harmonic distortion. By computing the power spectral density of watermarking halftone, we propose our method to adapt to the *total harmonic distortion* [13] for analyzing tonality, i.e. the signal power distribution over frequencies. The power spectral density (PSD), describes how the power (or variance) of a time series is distributed with frequency. Mathematically, it is defined as the Fourier Transform of the autocorrelation sequence of the time series. Let x is the signal of halftone image, the PSD is the Fourier transform of the autocorrelation function,$autocorr(\tau)$, of the signal if the signal can be treated as a stationary random process,

$$S(x) = \int_{-\infty}^{\infty} autocorr(\tau)\, e^{-2\,\pi\, i\, x\, \tau}\, d\tau. \tag{23}$$

$$PSD = \int_{F_1}^{F_2} S(x)\, dx + \int_{-F_2}^{-F_1} S(x)\, dx. \tag{24}$$

where the power of the signal in a given frequency band can be calculated in (24) by integrating over positive and negative frequencies.

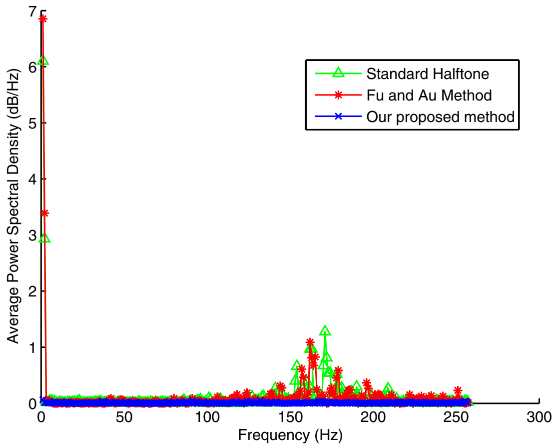


Fig. 7. Average Power Spectral Density of halftone boat images

The spectral density is usually estimated using Welch's method [20], where we define a Hann window to sample the signal x. To this end, we define the average PSD under a Hann window of 512 samples (two-side 256 sample dots)as

$$\overline{PSD} = \frac{1}{257}PSD. \tag{25}$$

For the Jarvis kernel, we embedded the surrey logo(90x112 bits) into the image *boat* of sizes 512x512. For $\overline{PSD}$ comparison, we analyzed the tonality of our proposed watermarking model compared with Fu and Au's method. The $\overline{PSD}$s of image *boat* are illustrated in Figure 7. As described in Section 3, our proposed model reduces the tonality of watermarked halftone images by adaptively adjusting K_w. This figure shows that Fu and Au's method(red line) generated higher $\overline{PSD}$ than the original halftone (green line). However, our method (blue line, while K_w=2.514) achieved $\overline{PSD}$ much smoother than the others. The same experiments were performed to all five images, and measured average power spectral desnity ($\overline{PSD}$) to all five images, as shown in Table 5. Where the K_w^1 in Table 5 is the initial value of K_w and the last K_w^{opt} is the optimum value of K_w. We found that image peppers's halftone has zero $\overline{PSD}$. This means its autocorrelation function is zero. However, when a watermark was embedded, it introduced harmonic distortion. The $\overline{PSD}$ for watermarked image peppers was approximately 0.0096 (dB/Hz) for both Fu and Au's method and our proposed method. Based on our model, we also found that the overall $\overline{PSD}$ of five images was reduced as K_w increased until it reached approximately $2K_w^1$. For example, image *boat*'s $\overline{PSD}$ reduces from 0.0893 (dB/Hz) (K_w^1=1.114) to 0.0096 (dB/Hz)(K_w^{opt}=2.514). We conclude that the lower the value and more uniformly distributed the $\overline{PSD}$, the lower would be the harmonic distortion. By finding an optimum K_w, the least distorted watermarked halftone image is

Table 5. Average Power Spectral Density

image	halftone	Fu and Au method	our proposed method (dB/Hz)	
peppers	0	0.0096	0.0096(K_w^1=1.035)	0.0096(K_w^{opt}=2.435)
boat	0.1053	0.1122	0.0893(K_w^1=1.114)	0.0096(K_w^{opt}=2.514)
barbara	0.2225	0.2185	0.2153(K_w^1=1.045)	0.1071(K_w^{opt}=2.445)
lena	0.0535	0.0521	0.0507(K_w^1=1.077)	0.0099(K_w^{opt}=2.477)
mandrill	0.1796	0.1914	0.1632(K_w^1=1.132)	0.0322(K_w^{opt}=2.532)

obtained. Therefore, an optimum perceptual quality is preserved via minimizing distortion in the data hiding error diffusion halftone images.

6 Conclusion

In this paper, we analyzed the perceptual distortion of watermarking embedding in error diffusion of halftone image. Two major impacts generated by data hiding error diffusion of halftone images have been clarified as: Firstly, sharpening distortion, as a consequence of the quantization error image being correlated with original grayscale image in the standard data hiding error diffusion; Secondly, the error diffused by *an error diffusion kernel* is distributed directionally in standard data hiding error diffusion process. It causes tonality, which results in strong cycle patterns. From our mathematical framework, we proposed the linear gain model for data hiding error diffusion halftoning and derived our optimized linear gain parameter K_w by mapping it to the halftoning linear gain model K_s. Theoretically, the K_w value has been estimated to be in the range of $[K_s, 2K_s]$. The increase of K_w towards variation of image quality quantified by WSNR was measured empirically using test images and results were presented. The optimum watermarked halftone image was found by choosing the maximum WSNR value. This model minimizes a significant amount of distortion resulting in 6.5% to 12% improvement of WSNR and 11% to 23% improvement of VIF, which finalized an embedded halftone image to be unsharpened and quantization error approximating an uncorrelated Gaussian white noise. This model adopted an iterative approach to minimizing the impacts of distortion in the data hiding error diffusion process without introducing the complexity $O(1)$. This minimized the differences between the grayscale image and the embedded halftone image. Consequently, the perceptual quality for halftone watermark embedding was found to be better than Fu and Au's method in terms of WSNR and VIF. The proposed linear gain control model was also validated using an average power spectral density.

Our future work will focus on robust watermarking approach for halftone image using error correction coding. Moreover, authentication and restoration will also be investigated.

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Appendix A

This appendix is derivation of the Equation L_w. In [12], the standard error diffusion transfer equation with signal transform function and noise transform function, can be expressed as z-transformation

$$Y(z) = \underbrace{\frac{K_s}{1+(K_s-1)H(z)}}_{STF} X(z) + \frac{1-H(z)}{1+(K_n-1)H(z)} N(z) \tag{26}$$

Replace Equation (12) into Equations (6) and (10). We obtain:

$$e(i,j) = 1 - y_0(i,j) - x'(i,j) \tag{27}$$
$$x'(i,j) = x(i,j) - h(i,j) * e(i,j) \tag{28}$$
$$x''(i,j) = x'(i,j) + L_w x(i,j) \tag{29}$$
$$y_0(i,j) = Q(x''(i,j)) \tag{30}$$
$$y(i,j) = 1 - y_0(i,j) \tag{31}$$

Substituting $x'(i,j)$ in Equation (28) into Equation (29), and taking z transform, we have

$$X''(z) = (1+L_w)X(z) - H(z)E(z) \tag{32}$$

From Equation (27) and Equation (28), taking the z transform, we have

$$E(z) = \frac{\frac{Z}{Z-1} - Y_0(z) - X(z)}{1-H(z)} \tag{33}$$

From Equation (32) and Equation (33), we derive

$$X''(z) = [1 + L_w + \frac{H(z)}{1-H(z)}]X(z) + \frac{H(z)}{1-H(z)}Y_0(z) - \frac{Z}{Z-1}\frac{H(z)}{1-H(z)} \tag{34}$$

In Figure 8, we draw the equivalent modified circuit to watermarking linear gain model. we obtain

$$e(i,j) = 1 - y_0(i,j) - x''(i,j) \tag{35}$$
$$x''(i,j) = g(i,j) * x(i,j) - h(i,j) * e(i,j) \tag{36}$$
$$y_0(i,j) = Q(x''(i,j)) \tag{37}$$
$$y(i,j) = 1 - y_0(i,j) \tag{38}$$

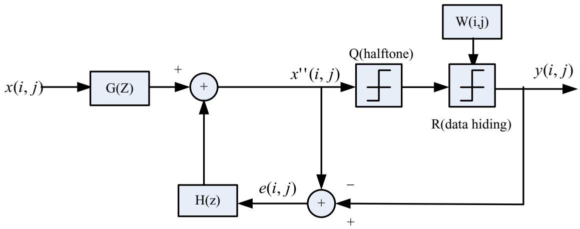


Fig. 8. Equivalent modified circuit

where $g(i,j)$ is an impulse response of G(z). From Equation (35) and Equation (36), we have

$$E(z) = \frac{\frac{Z}{Z-1} - Y_0(z) - G(z)X(z)}{1 - H(z)} \tag{39}$$

we substitute Equation (39) into the z-transform of Equation (36) ,we derive

$$X''(z) = [G(z) + \frac{G(z)H(z)}{1-H(z)}]X(z) + \frac{H(z)}{1-H(z)}Y_0(z) - \frac{Z}{Z-1}\frac{H(z)}{1-H(z)} \tag{40}$$

Equation (34) is equal to Equation (40),when

$$1 + L + \frac{H(z)}{1-H(z)} = G(z) + \frac{G(z)H(z)}{1-H(z)} \tag{41}$$

Then, we obtain

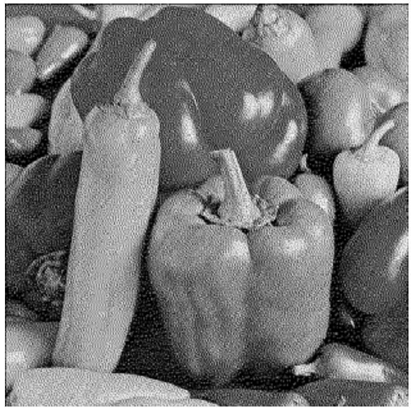
$$G(z) = 1 + [1 - H(z)]L_w \tag{42}$$

If we compare Equation (42) with the Signal Transform Function expressed in Equation (26),in which the watermarked halftone image with linear gain K_w has the same signal transfer function, G(z) can be expressed as the reciprocal of the STF. Thus,

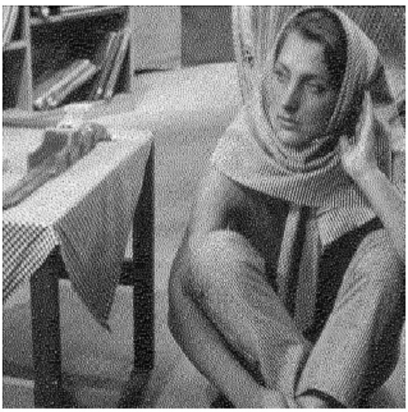
$$L_w = \frac{1 - K_w}{K_w} \tag{43}$$

□

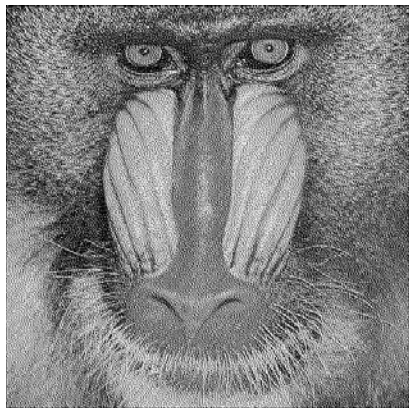
(a) our watermarked boat image, K_w=2.514



(b) our watermarked peppers image, K_w=2.435



(c) our watermarked barbara image,K_w=2.445



(d) our watermarked mandrill image,K_w=2.532

Fig. 9. Watermarked Halftone Images with Surreylogo 10080 bits embedded