Least Distortion Halftone Image Data Hiding Watermarking by Optimizing an Iterative Linear Gain Control Model

Weina Jiang, A.T.S. Ho, and H. Treharne

The Department of Computing
University of Surrey
Guildford, GU2 7XH, UK
W.Jiang@Surrey.ac.uk

Abstract. In this paper, a least distortion data hiding 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. 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. Our experiments show that the proposed linear gain model can achieve an improvement of between 6.5% to 12% as compared to Fu and Au's data hiding error diffusion method using the weighted signal-to-noise ratio(WSNR).

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 [11]. 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 [10] can be very useful in protecting printable halftone images for business, legal and law enforcement applications. Currently, there are two classes of data hiding methods proposed in the literature where (1) a watermark is embedded into a halftone image during an error diffusion process. In [2], 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 side to generate N pseudo random locations to be used for retrieving the watermark; (2) a watermark is embedded into two or more halftoning images, where the retrieval approaches can be overlays of halftone images [15] or using a look up table (LUT) to decode the watermark [12].

Halftone quality and robustness are the two main challenges for data hiding watermarking halftone images. The robustness of watermarking can be enhanced

Y.Q. Shi, H.-J. Kim, and S. Katzenbeisser (Eds.): IWDW 2007, LNCS 5041, pp. 423–439, 2008.

by incorporating error correction coding [4]. 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 preserve optimum 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* [13][6]. 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) [3]. 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 [13], i.e., error diffusion, dithering and iterative methods (Direct Binary Search). 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 [5] and Floyd and Steinberg [1]. 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 [2] 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. [12] 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. Wu [15] 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.

None of the above methods addresses the problem of minimizing the distortion to preserve the perceptual quality of an embedded halftone image. In this paper we propose a method which takes into account the effects of data hiding on the error diffusion halftoning process.

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 [7] 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 [6]. 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. [6] 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

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

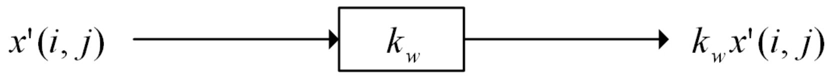


Fig. 1. Data hiding error diffusion linear gain model

where K_s is a linearization constant based on the uncorrelated white noise $n(i,j)$ assumption. 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. [6] error diffusion process and combine it with data hiding watermarking embedding. We begin by specifying K_w as a linear gain in Figure 1 (K_s represents a linear gain for standard halftone [6]) 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 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 [14].

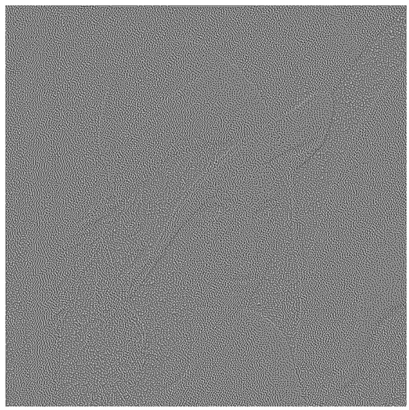
$$C_{EI} = \frac{|COV[EI]|}{\sigma_E \sigma_I} \tag{11}$$

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. Watermarke 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) [9] 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 watermarking 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 [6]. 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 watermarking 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. [6] 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

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

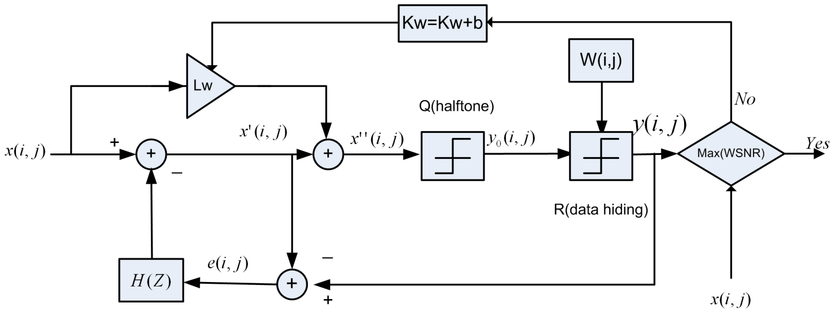


Fig. 3. Iterative linear gain halftone embedding

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

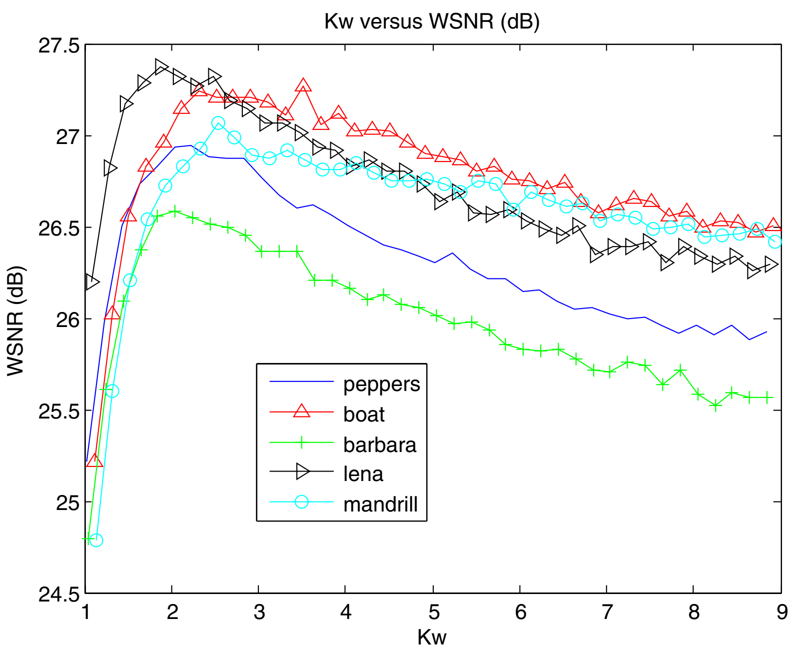


Fig. 4. The relationship between K_w and WSNR

block embeds one bit. Toggling halftone pixels is the same as Fu and Au's method [2] 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. Iteration starts from $K_w = K_s$ to process embedding in halftone, and loops by adding one additive amount b, i.e., $b = 0.2$ to K_w until the WSNR reaches the maximum.The relationship between K_w and WSNR is presented in Figure. 4, which illustrates the principle of the iterative algorithm. 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).

5 Experiments and Results Analysis

Modified Peak Signal-to-Noise Ratio (MPSNR) [2] and Weighted Signal-to-noise Ratio(WSNR) [6] 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 1 and MPSNR in Table 2. From Table 1, 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.

Table 1. 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

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

Table 2. 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

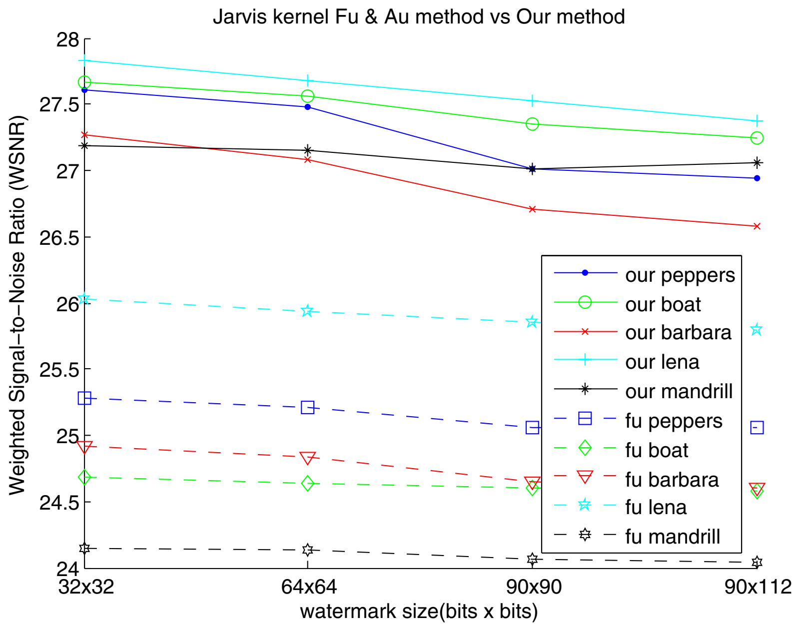


Fig. 5. WSNR of Fu method vs Our method

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 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 8.

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 [6] analogized the halftone distortion, which was caused by

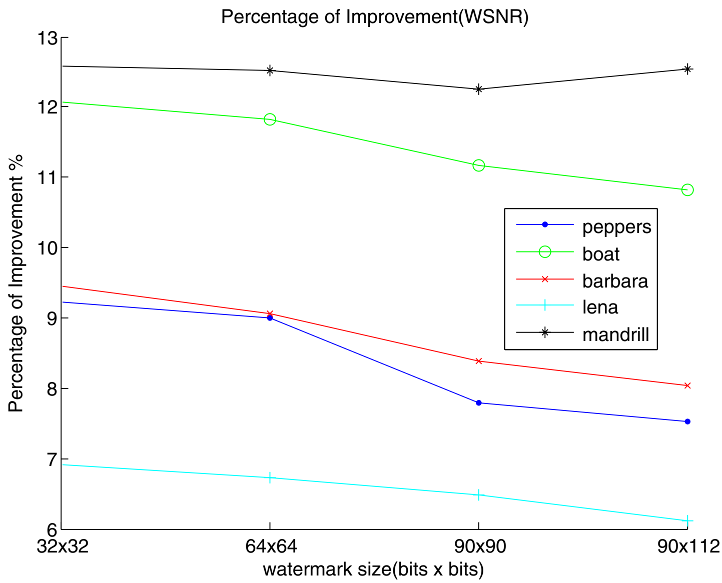


Fig. 6. Percentage of improvement of our method

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* [3] 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,

$$S(x) = \int_{-\infty}^{\infty} autocorr(\tau)\, e^{-2\,\pi\,i\,x\,\tau}\, d\tau. \tag{22}$$

$$PSD = \int_{F_1}^{F_2} S(x)\, dx + \int_{-F_2}^{-F_1} S(x)\, dx. \tag{23}$$

where the power of the signal in a given frequency band can be calculated in (23) by integrating over positive and negative frequencies.

The spectral density is usually estimated using Welch's method [8], 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

$$\overline{PSD} = \frac{1}{257} PSD \tag{24}$$

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

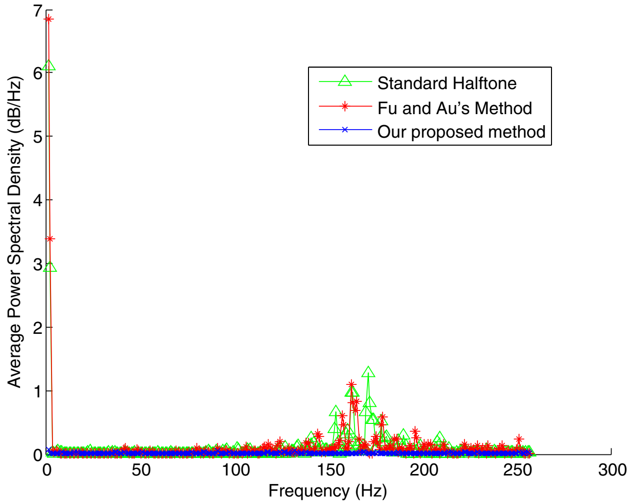


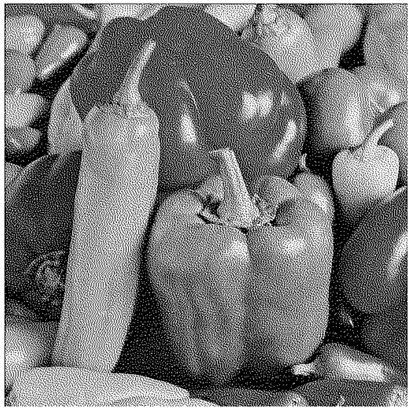
Fig. 7. Average Power Spectral Density of halftone boat images

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 3. Where the K_w^1 in Table 3 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

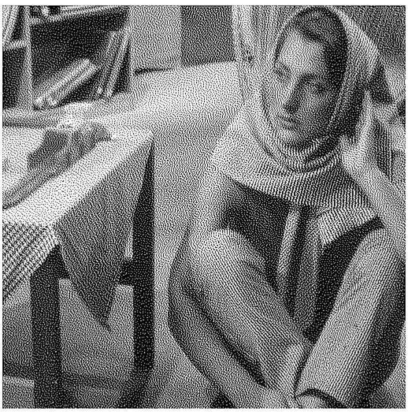
Table 3. Average Power Spectral Density

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)

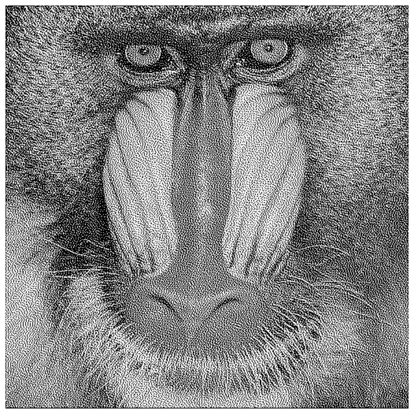
(a) our watermarked boat image, K_w=2.514



(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. 8. Watermarked Halftone Images with Surreylogo 10080 bits embedded

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 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 data hiding watermarking 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 watermarking 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. This model minimizes a significant amount of distortion resulting in 6.5% to 12% improvement of WSNR, which finalized an embedded halftone image to be unsharpened and quantization error becoming an uncorrelated Gaussian white noise. This model adopts an iterative approach to minimizing the impacts of distortion in the data hiding error diffusion process. In other words, it minimizes the differences between the grayscale image and the embedded halftone image. Consequently, the WSNR quality for halftone watermark embedding was found to be better than Fu and Au's method. 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.

Acknowledgments

We would like to thank Dr. Thomas D. Kite and Prof. Brian L. Evans from the University of Texas for their invaluable advice. We wish to thank Mr. Chris Culnane and Mr. Vinod Pankajakshan in our Watermarking and Multimedia Security group for their comments and feedback during the preparation of this paper.

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Appendix

This appendix is derivation of the Equation L_w. In [6], the standard error diffusion transfer equation with signal transform function and noise transform function, can be expressed as z-transformation

$$Y(z) = \underbrace{\frac{K_s}{1+(K_s-1)H(z)}}_{STF} X(z) + \frac{1-H(z)}{1+(K_n-1)H(z)} N(z) \tag{25}$$

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

$$e(i,j) = 1 - y_0(i,j) - x'(i,j) \tag{26}$$

$$x'(i,j) = x(i,j) - h(i,j) * e(i,j) \tag{27}$$

$$x''(i,j) = x'(i,j) + L_w x(i,j) \tag{28}$$

$$y_0(i,j) = Q(x''(i,j)) \tag{29}$$

$$y(i,j) = 1 - y_0(i,j) \tag{30}$$

Substituting $x'(i,j)$ in Equation (27) into Equation (28), and taking z transform, we have

$$X''(z) = (1 + L_w)X(z) - H(z)E(z) \tag{31}$$

From Equation (26) and Equation (27), taking the z transform, we have

$$E(z) = \frac{\frac{Z}{Z-1} - Y_0(z) - X(z)}{1 - H(z)} \quad (32)$$

From Equation (31) and Equation (32), we derive

$$X''(z) = [1 + L_w + \frac{H(z)}{1-H(z)}]X(z) + \frac{H(z)}{1-H(z)}Y_0(z) - \frac{Z}{Z-1}\frac{H(z)}{1-H(z)} \quad (33)$$

In Figure 9, we draw the equivalent modified circuit to watermarking linear

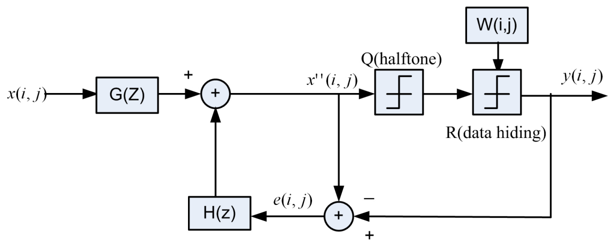

Fig. 9. Equivalent modified circuit

gain model. we obtain

$$e(i,j) = 1 - y_0(i,j) - x''(i,j) \quad (34)$$
$$x''(i,j) = g(i,j) * x(i,j) - h(i,j) * e(i,j) \quad (35)$$
$$y_0(i,j) = Q(x''(i,j)) \quad (36)$$
$$y(i,j) = 1 - y_0(i,j) \quad (37)$$

where $g(i,j)$ is an impulse response of G(z). From Equation (34) and Equation (35), we have

$$E(z) = \frac{\frac{Z}{Z-1} - Y_0(z) - G(z)X(z)}{1 - H(z)} \quad (38)$$

we substitute Equation (38) into the z-transform of Equation (35) ,we derive

$$X''(z) = [G(z) + \frac{G(z)H(z)}{1-H(z)}]X(z) + \frac{H(z)}{1-H(z)}Y_0(z) - \frac{Z}{Z-1}\frac{H(z)}{1-H(z)} \quad (39)$$

Equation (33) is equal to Equation (39),when

$$1 + L + \frac{H(z)}{1-H(z)} = G(z) + \frac{G(z)H(z)}{1-H(z)} \quad (40)$$

Then, we obtain

$$G(z) = 1 + [1 - H(z)]L_w \tag{41}$$

If we compare Equation (41) with the Signal Transform Function expressed in Equation (25),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,

$$L_w = \frac{1 - K_w}{K_w} \tag{42}$$

□