An Optimization of Digital Halftoning Using Content Sensitive Adjustment

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ABSTRACT

A method to generate optimal halftone images using content sensitive adjustment is proposed. There are two steps to implement the algorithm. First, adjust intensity of each gray level to be equal between initial halftone image and con-tone image. Secondly, use direct binary search (DBS) to minimize the difference between con-tone image and halftone image as perceived by human eyes. After a number of iterations, an optimization halftone image can be achieved. The algorithm differs from that in conventional DBS by exploiting the equality of the gray value locally in the corresponding region between con-tone and halftone image allowing the rendition to preserve the appearance perceived similarly. By local processing, the algorithm can improve the quality of the halftone image and decrease the computation cost in frequency weighted mean square error. Besides, it can also reduce the visual artifact effect of the initial halftone image's quality on the manipulated halftone image.

1. INTRODUCTION

Halftoning is a final and most computationally intensive process in the imaging pipeline associated with desktop printer that represent 8-bit/pixel continuous-tone image data for each color plate by means of either one bit or a reduced number of bits. In terms of the variation of rendering dot size and the dot placement space, the human visual system illusively perceives the rendered pattern as continuous-tone image. That is because human eyes have the characteristic of a low-pass filter, and that is why we can treat increasing or decreasing cluster dots as continuously. There are many approaches proposed to improve the quality of halftone images to make halftone images to be perceived similar to its original con-tone ones.

According to the computational structure, digital halftoning algorithms can be divided into three classes [16]. The first class is the point process. The halftone images are generated by pixel wise comparing the con-tone images and pre-designed periodically repeated threshold matrix. The screening is the typical one. The second class exploits the neighbor pixel as the diffusion of the current quantization error, such as the error diffusion. The third class of the algorithms is an iterative approach to yield an better

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image quality, such as direct binary search [15]. From the first to the second and the third class, the image quality increases while the computation complexity also increases. DBS is generally regarded as the gold standard for halftone quality, but it has never been directly used in a product due to its computational complexity. Hence, the aim of the proposed method attempts to resolve the limitation in DBS computational complexity.

In this paper, a new algorithm is proposed that based on DBS and con-tone image distribution of gray level to get a better image in quality, and save more computation time.

2 DIGITAL HALFTONING

Because of the limit of output devices, they have to use binary pixels to simulate continues tone images. Human visual system shows that the perceived scenes can be con-tone illusively by increasing of decreasing cluster dots continuously due to the property of low pass filter in human visual system.

In this section a number of halftone approaches and their evolution is introduced such as fixed-level quantization, noise adding before screening, order dithering, error diffusion, and blue noise mask[1][4].

2.1 FIXED-LEVEL QUANTIZATION

This is the simplest and fastest way among the existing halftone approaches. It quantizes continuous tone image depending on a fixed gray level as threshold value. If the tone value of the pixel in original image is larger than threshold value, it will be quantized to be one. On the other hand, the pixel will be quantized to be zero.

The main disadvantage of this approach is the poor quality visually which is due to the most quantization error in images are accumulated in the middle tone during the halftoning process resulted as unpleasant high contrast.

2.2 NOISE ADDITION

In order to disturb the accumulated error in the middle tone by fixed-level quantization halftoning process, the similar gray value relation existing in neighbouring pixels has to be de-correlated. Thus, it leads to decrease high contrast in halftone images. Toward this end, noise is added before halftoning and it can also set a random threshold value when applying halftoning.

There is a problem that the halftoned images look noisy, although the qualities of halftone images have been improved. Moreover, a noise addition has essentially erupted the image perception quality, to recover the image by processes afterward leading to the halftone task more difficulty. On the other hand, disturbing the correlation among the neighbouring pixels raises the idea of the screen pattern design with screen values distributing in stochastic manner described as following.

2.2 ORDER DITHERING

To reduce the correlation, order dithering is another approach to improve the quality of halftone image. There are two steps during halftoning process: first is to design an ordered mask, and second is to quantize images depending on the values of the corresponded pixels in the mask and with different ways to generate the mask, there are two main kinds of the mask: cluster and dispersed dithering. Both dithering mask designed follows the principle that threshold value determined with stochastic pattern to meet the demand of the perception quality.

2.2.1 CLUSTER DITHERING

The threshold values of the mask pixels increase from center to edge of the mask.

Images halftoned with this approach will still result in obvious pattern visually, even though it is better than noise adding. Figure 2 (D) shows that a con-tone image with values between 0 and 1 is halftoned by using cluster dithering.

2.2.2 DISPERSED DITHERING

This approach is similar to cluster dithering with one difference that threshold values of the pixels on the mask distribute uniformly.

Dispersed dithering is generated to reduce low frequency component in image spectral which is due to noticeable texture pattern often exhibited within low frequency component of human visual system. As a result, the dispersed dithering is perceived sharper than the cluster dithering in keeping information in image edge. But it usually introduces more dot gain than cluster dithering because of more dot boundaries.

2.3 ERROR DIFFUSION

Error diffusion is useful to diffuse errors during halftoning, and it can improve the un-sharp problem happened when doing dispersed dithering. Because this approach do best of its ability to keep the tone values, it can show more details than others mentioned previously[3].

Each computing pixel has been diffused errors from those have been quantized before quantizing, and there is a flow chart shown blow:

The most problem of error diffusion is that it will also generate visible texture, and there are also many improvements have been proposed. Figure 1 shows that a con-tone image with values between 0 and 1 is halftoned by using error diffusion.

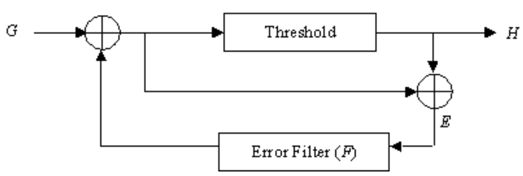

Figure. 1 Flow chart of an error diffusion scheme

In Figure 1, G is the original image, H is halftoned image, quantization error E is diffused to neighbouring pixels through filter F.

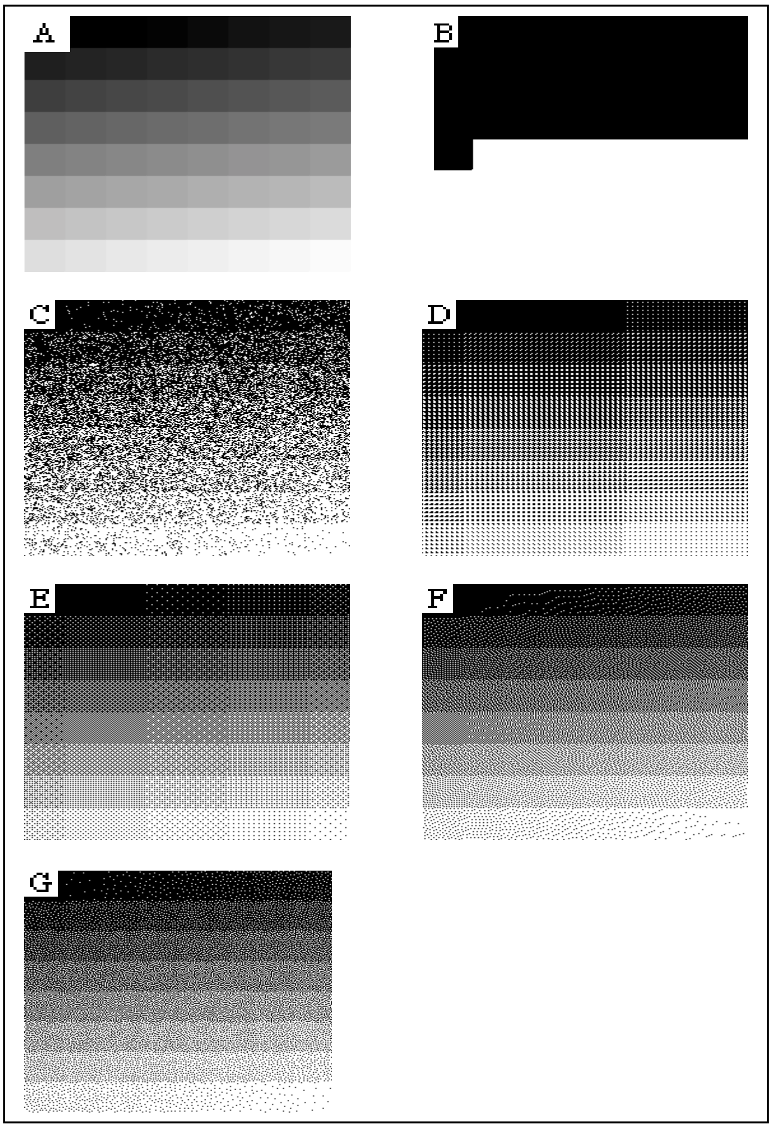

Figure. 2 Halftoning approaches (A)testing image (B)Fixed-Level Quantization, (C) Noise Addition, (D)Cluster Dithering, (E)Dispersed Dithering , (F)Error Diffusion, and (G)Blue Noise Mask.

2.4 BLUE NOISE MASK

A blue noise mask designed such that a rendered halftone image has high frequency spectral component and almost attenuate at low frequency spectral. Because that the pixels are distributed among high frequencies, it has good quality in visual [2][5][7]. There are two steps to generate halftone images. It generates blue noise mask in the first stage, and then halftoning the contone image like order dithering. In general, a blue noise mask is generated from a white noise mask initially. Then convert the white noise mask to a blue noise mask by using Void-and Cluster proposed by Ulichney, [8].

Blue noise mask is effective in image halftone. It can generate different mask size for different con-tone images accordingly [6].

In figure2, a ramp image size of 256x256 is used as testing to demonstrate the evolution of the halftone approaches. The middle tone due to threshold can be simulated better increasingly along the trend.

3. THE OPTIMAL HALFTONE ALGORITHM

In this paper, the HVS is incorporated with image characteristics to propose an optimum halftone algorithm. This approach can keep the intensity of grayness equality between con-tone and halftone images. This algorithm is based on direct binary search (DBS) to both reduce the errors and reduce the computation complexity.

A search-based approach based on the direct binary search (DBS) heuristic has also been proposed by Analoui and Allebach[10]. Similar algorithms were pro-posed by Pappas and Neuhoff [12] and Mulligan and Ahumada.[13] DBS accounts for the characteristics of the printer and human visual system. images on such devices. Carrara et al [14] suggested a combination of DBS and pulse density modulation to improve the quality of halftones generated by DBS at extreme absorptances. Lieberman and Allebach [15] suggest different search heuristics for achieving better quality. DBS generates halftones that are visually pleasing and have fewer artifacts. The reason it outperforms other techniques is that it is iterative and there is no causality constraint.

The flow chart of optimal halftone algorithm is shown as figure 3.

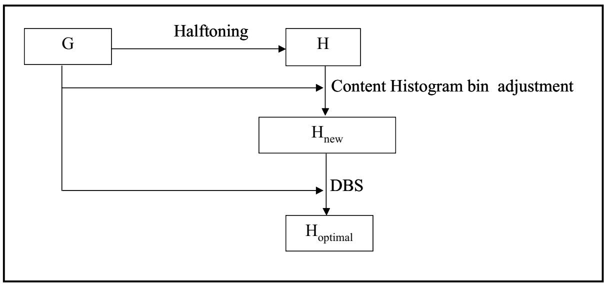

Figure. 3 Block diagram of Intensity of Grayness based halftoning algorithm

In figure 3, G is a con-tone image, H is a halftone image, H_{new} is the modified halftone image, H_{optial} is the optimal halftone image.

3.1 Equal intensity of grayness

One of criterion to evaluate the quality of halftoned image is to compare the average of the gray level value locally in halftone image against that in original image. For illustrating purpose, in initial halftone image the sum of gray level value is incorporated and termed as Intensity of Grayness (IOG).

It is observed from that human visual system treats clusters of dots as a continuously gray level. In such manner, the equal IOG between con-tone and initial halftone images leads halftone process toward a directly and robust way to render image more efficiently. In addition, the dithering approaches approximate the halftone result by dithering based on the same average mean gray level in the region between con-tone and halftoned image. As the result, we propose to keep the number of halftone absorption of dots equal to the gray value of corresponding region in original image. To edetail this, for example, there is a constant gray level image size of 128x128, and with constant gray value 0.25. The initial halftoned images obtained by different approaches mentioned before. The sum of IOG of each initial halftone is shown in Table 1.

Table. 1 Sum of IOG of various halftone schemes

Halftoning Approaches	Sum of IOG
Original	4096
Fixed-Level Quantization	*0*
Noise-Adding	*4117*
Cluster Dithering	*3072*
Dispersed Dithering	*3584*
Error Diffusion	*4119*
Blue Noise Mask	*4124*

The table shows that sum of IOG of halftone images are not sourly equal to that of original con-tone image. Since the IOG of most halftoned image is not equal to original image leads us to develop a new halftone algorithm by adjusting the IOG of halftone image accordingly based on FWMSE. In order to detail the process, figure 4 shows the procedure.

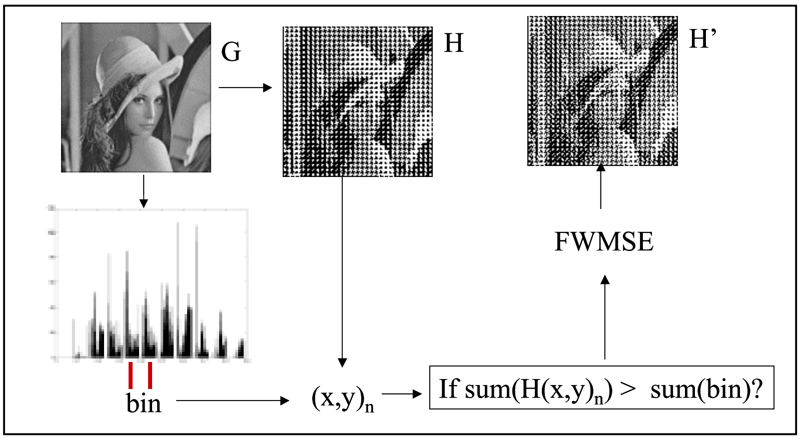

Figure. 4 The flow chart of the content based adjustment halftone

In figure 4, G is the original image, H is the initial rendered halftone image, $(x,y)_n$ is the pixel value at region n.
During the adjustment, we first divide IOG into 100 levels in con-tone image, and match each level's corresponding locations in halftone image. Second, for each level, if the IOG is larger than that of con-tone image, we toggle current pixel that with larger error metric. In this work the frequency weighted mean square error, FWMSE, is employed. The procedure is to search the larger error pixel whiles to keep the intensity of gray level being equal in the region of the input and output images until each level has equal IOG.

3.2. Human visual system and error function

Human Visual System (HVS) is a model to approximate human perception. The model is used to assess the quality of halftone images. Error Function guides to know how the halftone image similar to its original con-tone image, and generally there are several functions such as Mean Square Error (MSE), Absolute Error and Frequency Weighted Mean Square Error (FWMSE).

3.2.1 Human visual system

HVS is a model that simulates human visual, and measures the fidelity between con-tone and halftone image[6]. Compbell[9] proposed modeling Contrast Sensitivity Function by taking sine signals of human visual with a uniform background. It is defined as:

$$CSF(f) = k(e^{-2\pi f \alpha} - e^{-2\pi f \beta})$$

where *CSF(f)* is the contrast sensitivity function, *f* is the special frequencies, *k* is a constant which is proportional to illuminance, and there are empirical constants, α and β are 0.012 and 0.046 respectively (Analoui [10]). Generally, the special frequency f_{max} obtained as follows is normalized to be 1.

$$\begin{cases} f = f_{max} = \dfrac{\ln(\alpha/\beta)}{2\pi(\alpha-\beta)} \\ CSF(f_{max}) = 1 \end{cases}$$

As the result, we get relations among visual angles θ (degree), distant of measurement D (inch), and resolutions of device R (dot per inch, dpi) shown as below:

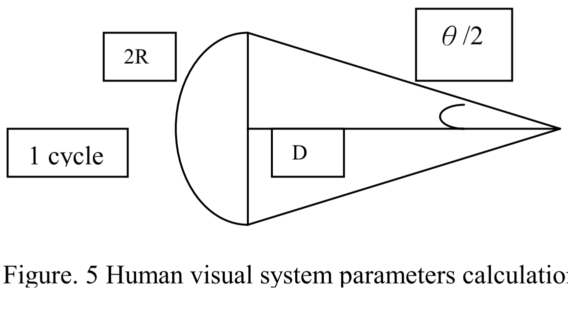

Figure. 5 Human visual system parameters calculation

$$\theta = 2\tan^{-1}(\frac{1}{2RD}) \approx \frac{1}{RD}(\text{radians}) = \frac{1}{RD} \times \frac{180}{\pi}(\text{degrees})$$

$$f = \frac{1}{\theta}(\text{cycles / degree})$$

Daly proposed a 2-D HVS that include the characteristic of non-isotropy of human visual, and it is defined as:

$$CSF_{2D}(f, f_\theta) = CSF'(\frac{f}{0.15\cos(4f_\theta)+1.35})$$

In our paper, we assume that distant of measurement is 20 inches, and resolutions of device is 300dpi.

3.2.2 Error function

We use FWMSE to estimate the similarity between halftone image and original con-tone image in this paper[9]. FWMSE is the improved type of MSE that take account of Human Visual (Frequency Weighted) defined as:

$$e(x,y) = \left[\sum_{k=-\frac{p}{2}}^{\frac{p}{2}} \sum_{l=-\frac{q}{2}}^{\frac{q}{2}} V(k,l)[G(x-k, y-l) - H(x-k, y-l)] \right]^2$$

$$FWMSE = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} e(x,y)$$

Where G(x,y) is a con-tone image with size M by N, H(x,y) is the halftoned image with size M by N, V(k,l) is a weight mask with size p by q, and e(x,y) is the error.

3.3. Direct binary search (DBS)

DBS is an approach that improves any un-optimal halftone image by using iteration, and according to error of human perception to find optimal halftone image[10][11][12].

The flowing flow chart in Figure 6 shows how DBS processes each pixel:

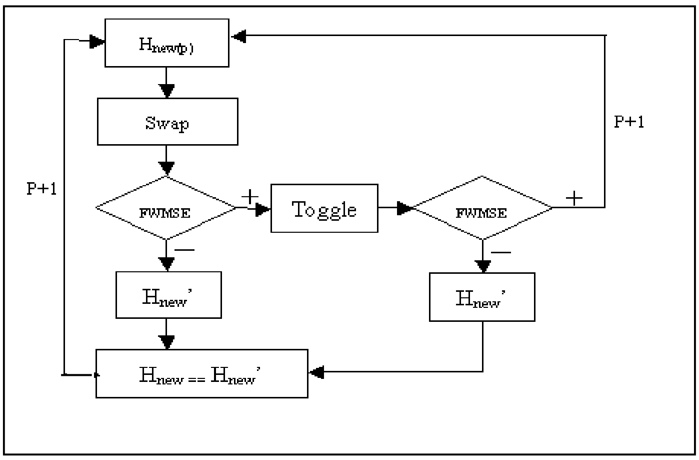

Figure. 6 Flow chart of direct binary search halftoning

In figure 6, the phase P of the current pixel in initial halftone image is investigated acoording to the FWMSE criterion. The current pixel is swapped with corresponding different pixel with larger computational error iteratively. The iteration stops when the error is within tolerance. The toggling is applied to the current pixel similarly. Swap and toggle detail can be refered to work in [15]. The swap and toggle process pixel by pixel iteratively, until no swap or toggle is accepted. Thus, a new halftone image H'_{new} can be obtained which has less errors than H_{new}. Further reduction of the complexity in DBS is implemented by means of block wise manner. The intensity of the grayness is adjusted as the same between the con-tone and

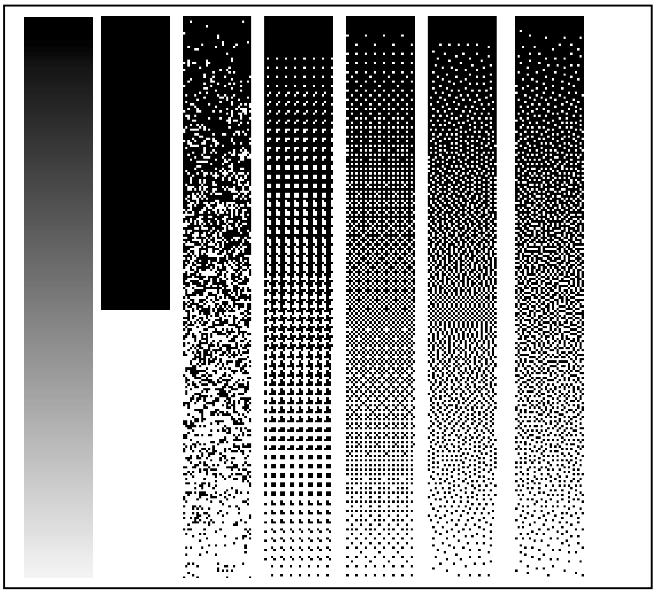

Figure. 7 The halftone results before doing DBS

halftone image in the range of the corresponding block.

4 RESULTS AND DISSUSION

We implement DBS using the reviewed halftoning approaches in the order of Fixed-Level Quantization, Noise-Adding, Cluster Dithering, Dispersed Dithering, Error Diffusion, and Blue Noise Mask. Figure 7 and Figure 8 show the results of different halftoning approaches before and after doing only DBS. Figure 9 shows the result that is the halftoned gray scales by applying DBS with proposed optimal algorithm. In these figures, the gray scales image arrange from left to right ordered as original con-tone gray scale, Fixed-Level Quantization, Cluster Dithering, Dispersed Dithering, Error Diffusion, and Blue Noise Mask.

Table 1, 2 and 3 show the FWMSE of these halftone gray scales from figure 2 to figure 4, and we can find that the errors are significant reduced after doing DBS.

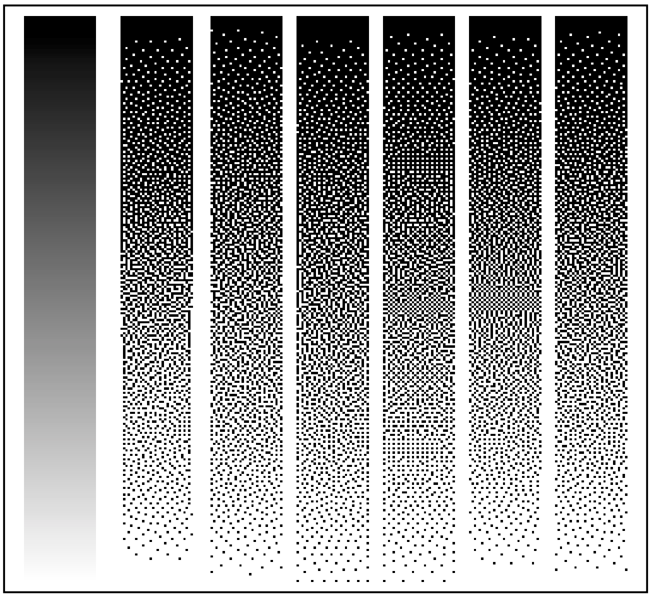

Figure.8 The halftone results of after doing DBS algorithm

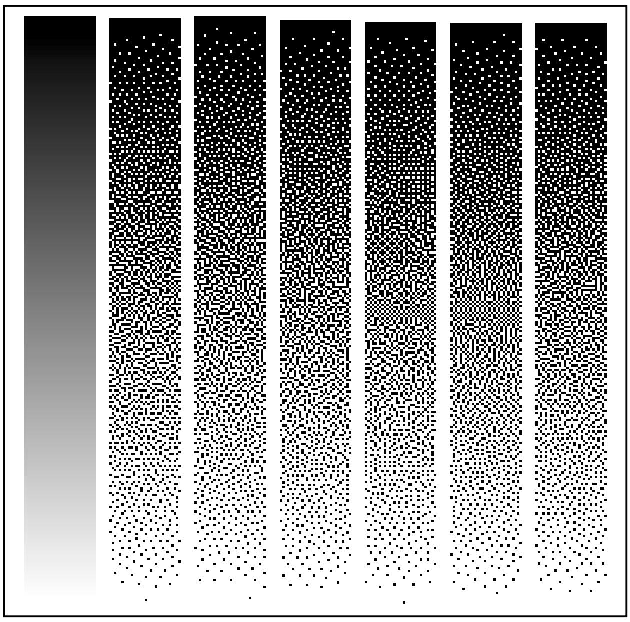

Figure. 9 The halftone results after doing DBS by using our optimal halftone

Table 2: FWMSE of different halftoning approaches before doing DBS

Halftoning Approaches	FWMSE
Fixed-Level Quantization	640.7202
Noise-Adding	58.5414
Cluster Dithering	26.7558
Dispersed Dithering	5.4002
Error Diffusion	2.4942
Blue Noise Mask	3.8746

Table 3: FWMSE of different halftoning approaches after doing DBS

Halftoning Approaches	FWMSE
Fixed Level Quantization	6.0963
Noise Adding	2.3732
Cluster Dithering	5.9158
Dispersed Dithering	3.0738
Error Diffusion	1.5476
Blue Noise Mask	1.6556

Among table 2 to 4, we can find that our optimal halftone algorithm has less FWMSE than other approaches, and that is because of our adjustment proportion of gray levels depending on distributions of original con-tone images. In addition, our algorithm is independent of original halftone image, and the quality can be better than those just using DBS which is depend on original halftone images. Figure 10 and figure 11 show the process of DBS and the proposed optimal halftone algorithm in several halftoning phase.

In Figure 12, the Lena image is used as the testing image. Followed by the Floyd Steinberg error diffusion filter, the halftone result shows fine detail as in Figure 13. Figure 14 shows the proposed accelerate direct binary search with promising result. Note that the artifact texture existing in Figure 13 as a drawback mentioned in normal error diffusion has been reduced.

Table 4: FWMSE of different halftoning approaches after doing DBS by using proposed optimal halftone algorithm

Halftoning Approaches	FWMSE
Fixed-Level Quantization	1.7653
Noise-Adding	1.7649
Cluster Dithering	1.7651
Dispersed Dithering	1.6766
Error Diffusion	1.4509
Blue Noise Mask	1.5658

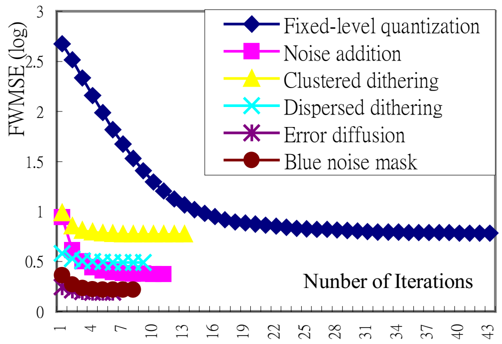

Figure. 10 the process of DBS in several halftoning ways

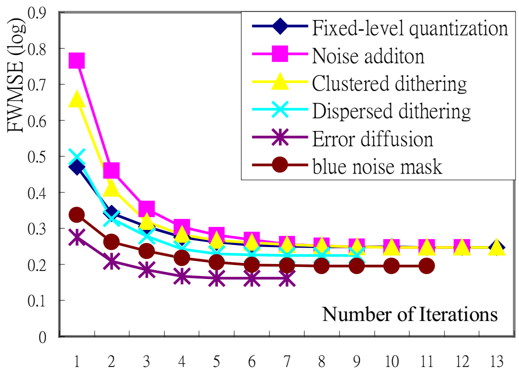

Figure. 11 the process of proposed optimal halftone algorithm in several halftoning ways

We can find that the decrease of FWMSE in our optimal halftone algorithm is faster than that in DBS, and it is also because that our adjustment of IOG. The adjustment can generate a better pixel arrangement than initial halftone image.

5 CONCLUSIONS

In this paper, evolution of the halftone process is introduced. Some of the observations are summarized that to reduce the accumulated error due to the thresholding the de-correlation can be achieved by incorporating the stochastic screen design. Particularly, the ordered dithering is to keep the average intensity level between input and output images by using various thresholds. The average intensity retained in dithering motivates the equal of intensity of grayness. In order to generate a high quality of halftone image, we use the ideal of "Equal of IOG", and use HVS and FWMSE to modify initial halftone images. After modifying, the new halftone image has equal intensity of grayness distributions with con-tone image. By applying DBS, we can find the better result with lower error. The proposed optimal halftone algorithm can improve halftone image quality and reduce the errors between con-tone image and halftone image as promising.

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Figure. 12 Lena 256x256 input image

Figure. 13 Floyd Steinberg error diffusion halftoned result

Figure. 14 Proposed method applied to input image