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Texture-aware Error Diffusion Algorithm for Multi-level Digital Halftoning

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Abstract. *Digital halftoning is a technique for converting a continuous-tone image into a quantized image to reproduce it on a digital printing device. Error diffusion (ED) is an algorithm that has proven to be effective for the halftoning process, and it has been widely applied to digital printing tasks. However, in images reproduced using conventional ED algorithms based on the signal processing theory, the texture of objects is often lost. In this study, we propose a texture-aware ED algorithm for multi-level digital halftoning. First, we generate multiple mapped images with different brightness levels through nonlinear transformation. For each mapped image, we adopt a texture-aware binary error diffusion method to obtain multiple halftone images. Finally, we generate a multi-level halftone image from the multiple halftone images. We test the algorithm on an actual printer, compare the results with those of the current raster image processor software and classical ED algorithms, and observe that our algorithm outputs better results.*

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1. INTRODUCTION

Digital halftoning is an important method for representing a grayscale image using only black and white tones. Error diffusion (ED) belongs to the class of frequency-modulated halftoning techniques. It is widely used because it can retain the details of an image while using a limited gray level to simulate a continuous-tone image. A detailed description and analysis of this algorithm can be found in Ref. [1–3].

Multi-toning is a halftoning method that adopts more than two tone levels for improving the similarity between the original and halftone images. The simplest method for this process is to increase the number of threshold values in the ED process.

Recently, the representation of the "texture" of an image, which includes properties such as its glossiness, transparency, and roughness, has become important for reproducing images on display devices. However, the texture of objects is often lost in images reproduced using conventional ED algorithms based on the signal processing theory, and there has been limited discussion regarding the reproduction of texture in printing.

In this study, we propose a texture-aware ED algorithm to improve the quality of texture in multi-level halftone images. In the proposed algorithm, we generate multiple mapped images with different brightness levels through nonlinear transformation. For each mapped image, we adopt a texture-aware binary ED method to obtain multiple halftone images. Finally, we generate a multi-level halftone image from the multiple halftone images.

We compare the results of the proposed algorithm with those of the Floyd [3], Shiau [4], and classical algorithms and verify its feasibility.

2. RELATED WORKS

Error diffusion, proposed by Floyd and Steinberg, is one of the most popular halftoning methods as it is simple and fast and it provides excellent results by retaining the details of the original image. There are several improved algorithms based on the Floyd algorithm (e.g., by Stucki [5] and Bayer [6]). These algorithms have been used to redesign the mask in ED to obtain better halftoning technology. Additionally, there are many other approaches to improve ED. One of the simplest techniques for improving the halftoning quality is to change the scanning direction and ED masks. This approach, alternately scanning left to right and right to left, is called serpentine scanning. There are also methods to reduce banding effects by adding random noise into the input or the threshold [6]. A theoretical analysis of the stability of different output patterns can be found in the work by Zhou [7].

Some studies have been conducted with a focus on the quality loss at edges due to the ED algorithm. Fung and Chan [8] and Li [9] used algorithms that focused on edges and led to edge-preserving ED techniques. In these studies, edge information was directly used. In other approaches for improving the quality of quantized images using edge

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information, Pang et al. [10], Lee et al. [11], Shi and Li [12], and Kiyotomo et al. [13] focused on weak textures vanishing in the quantization process and proposed halftoning algorithms to preserve these weak textures using edges. The objective of their methods was to emphasize edges that disappeared in the printing process.

Multi-level algorithms were developed by Sarailidis and Katsavounidis [14], Guo et al. [15], and Fung and Chan [8], who modified the halftoning ED algorithm to include multi-toning. However, in these previous studies, actual printed images were not evaluated and the adverse effect of the expansion of black areas due to machine noise was not considered. There are some half-level algorithms using printer models. Pappas et al. [16], Lee et al. [17], and Lai et al. [18] proposed halftoning algorithms that focused on dot gain and overlap of ink. Yampolskiy et al. [19] proposed a special halftoning algorithm based on the genetic algorithm. Their methods were proposed for natural images and mainly improved reproduction in factors such as color and unwanted patterns. Therefore, their goals were different from ours. We focus on the reproduction of the texture of objects.

3. TEXTURE-AWARE ED ALGORITHM

To detect pixels that are related to the texture, we construct a texture-preserving ED algorithm using a novel function.

3.1 *ED Algorithm for Binary Digital Halftoning*

In this section, we propose an ED algorithm for binary digital halftoning to preserve the texture of the objects in the image.

We assume that the texture of the proposed algorithm is highly dependent on the texture representation of the image content. Therefore, we consider a texture-preserving approach to effectively preserve the texture of objects. We also prepare different weights for the error distribution between the texture and other regions to permit stable detection of texture pixels. We use a novel function to implement the proposed texture-aware ED algorithm to detect pixels related to the texture of the image.

To explain the algorithm, we first need to briefly introduce the flow of the typical ED. X, Y, and E represent an 8-bit input image, the quantized output image, and the error image, respectively. $X(i, j)$ denotes the (i, j)th element of the image matrix. The ED algorithm processes the pixels from left to right in laser scanning order. Furthermore, we use the ED mask by Shiau and Fan in the algorithm. We describe the ED process as follows:

$$Y(i, j) \Leftarrow Q(X(i, j) + E(i, j)), \tag{1}$$

where $Q(x)$ is a quantization function defined by

$$Q(x) = \begin{cases} 0, & x < 128 \\ 255, & 128 \leq x. \end{cases} \tag{2}$$

Thus, the quantization error can be calculated as

$$e \Leftarrow X(i, j) + E(i, j) - Y(i, j). \tag{3}$$

The error is diffused to the neighborhood pixels by mask M. On renewing error image E, we apply the procedure to the subsequent pixels.

In principle, the typical ED algorithm distributes the error regardless of the presence of the pixel of interest in the texture portion. In this binary ED algorithm, the original image is preprocessed by obtaining the texture information from it. Therefore, the detected texture information is preserved by means of ED. In image processing technology, there are several methods for texture detection such as Canny, Sobel, and Laplacian techniques. However, in this binary ED, we use a detection and enhancement method to calculate texture information. First, a Sobel filter is applied to the original image to calculate the intensity of edge $I_e(i, j)$. Next, to exclude contour information from the information of detected edges, we calculate the edge variance $I_\sigma(i, j)$ of the surrounding pixels. Therefore, the texture information can be calculated as

$$Ti(i, j) = I_e(i, j)\left(1 - F\left(\frac{I_\sigma(i, j)}{\max I_\sigma}, g, \theta\right)\right), \tag{4}$$

$$F = \frac{1}{\exp(-g(x-\theta))}, \tag{5}$$

where the parameters of the s-curve function are empirically obtained and are set as $g = 16$ and $\theta = 0.2$.

During the execution of the ED algorithm, we quantify the pixel that carries the detected texture information. To ensure that the error is not spread to the pixels that belong to the strong texture, we redesign the structure of classical ED (Figure 1). As shown in Figure 2, this process is applied to all the pixels of the image in the direction of the raster.

To illustrate the quantification process in further detail, we define a modified error image $E'(i, j)$. Thus, the quantized image can be represented as

$$Y(i, j) \Leftarrow Q(X(i, j) + E'(i, j)), \tag{6}$$

where the error image E' is calculated by

$$E'(i, j) \Leftarrow E(i, j) \times Ti(i, j). \tag{7}$$

This process is represented as *diffuse*(E, Ti) in Fig. 2. Thus, the quantization error can be calculated as

$$e' \Leftarrow e + e'', \tag{8}$$

where e and e'' can be, respectively, represented as

$$e \Leftarrow X(i, j) + E'(i, j) - Y(i, j), \tag{9}$$

$$e'' \Leftarrow (1 - Ti(i, j)) \times E(i, j). \tag{10}$$

As shown in Eqs. (9) and (10), for the normal quantization error e, we add the cumulative error e'', which

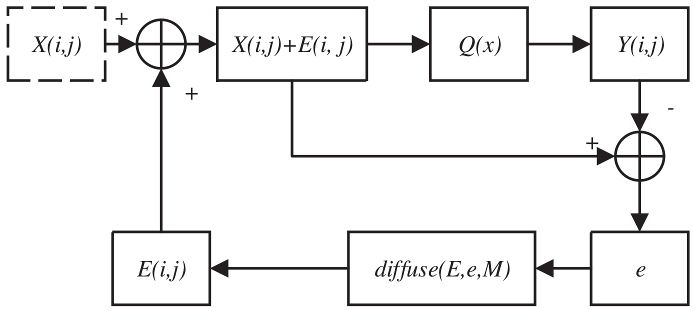


Figure 1. Outline of classical ED algorithms.

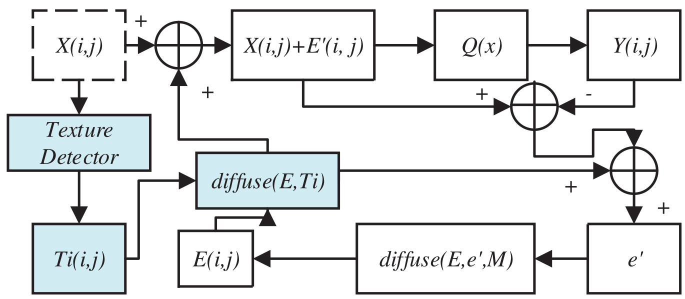


Figure 2. Outline of the quantization process of the proposed ED algorithm.

is not distributed according to the density of the texture. Figure 3 shows the original image and the detected edge information.

3.2 *ED Algorithm for Multiple Digital Halftoning*

Based on the algorithm described in the previous section, we extend the method to multi-level ED. Figure 4 shows the flowchart of the proposed method. The extension method is a nonlinear transformation based on tone mapping. Because the result of nonlinear correction can highlight the level of the image, these levels often have different gray levels. These different levels are then halftoned and finally synthesized, thereby avoiding the artifacts caused by the classical algorithm. Thus, for a grayscale image, we first perform multiple nonlinear transformations and generate multiple mapped images with different brightness levels. Next, we perform binary ED processing on the results of the nonlinear transformation. Finally, utilizing a certain strategy, we use the results generated in the previous step to synthesize the results of multi-level ED.

For multi-level halftoning that is directly extended from binary halftoning, a "contour" artifact often appears in gray transition areas. In these areas, there is less error diffusion, resulting in no change in the pixel value after halftoning; then a continuous contour is produced. To discretize the continuous gray value area, we choose an exponential function for image transformation based on the idea of expanding and compressing the image gray value. This is because the exponential function can expand the high gray level of the image and compress the low gray level of the image.

As an example, we explain 2-bit digital halftoning. In Figure 5, $X'(i,j)$ can be defined as

$$X'(i,j) = \begin{cases} (X(i,j))^{\frac{1+m}{2-m}} & \text{if } m \leq 0.5 \\ 1-(1-X(i,j))^{\frac{1+m}{2-m}} & \text{otherwise,} \end{cases} \tag{11}$$

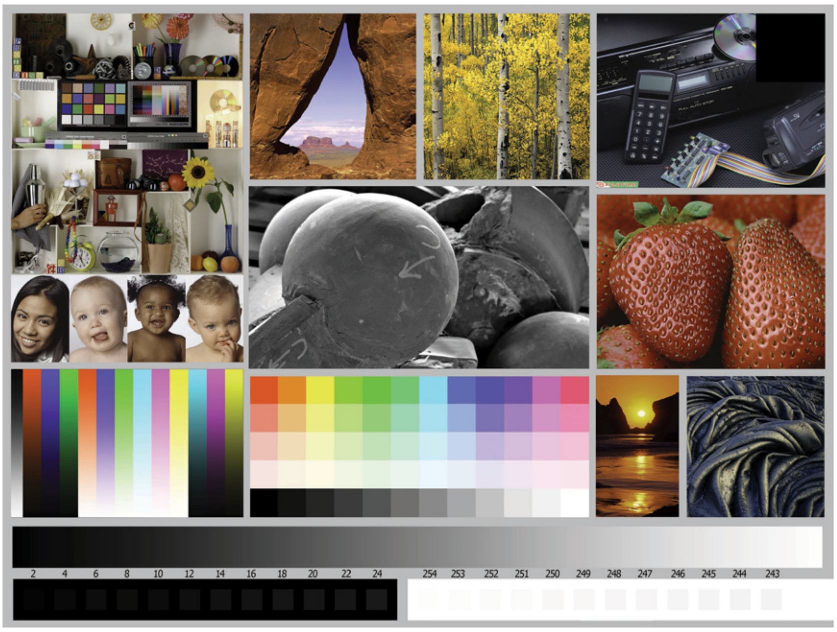
where m is the intermediate level determined to minimize the root-mean-square errors of the multi-level halftone and original images.

Two mapped images X_B and X_W with different brightness levels are calculated using functions $f1$ and $f2$:

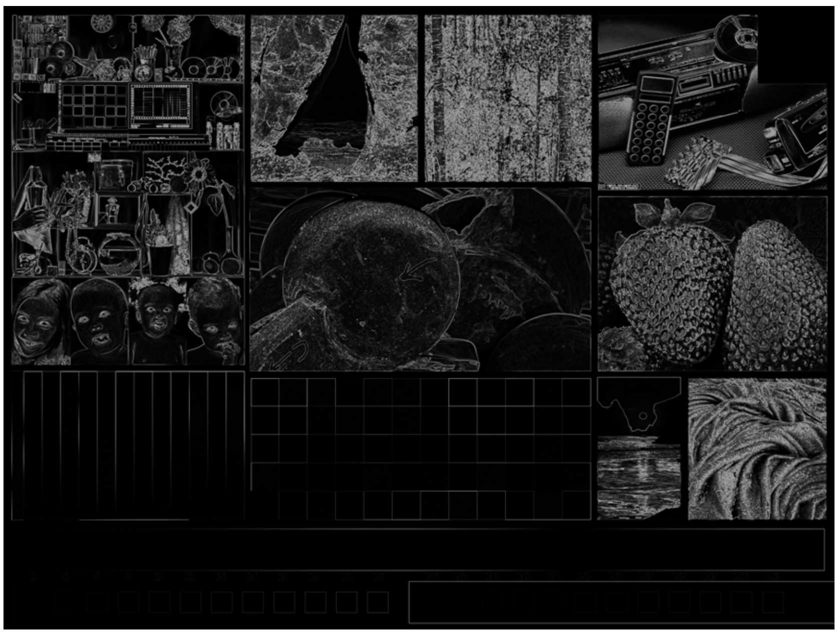
$$f1\colon X_B(i,j) = (X'(i,j))^2, \tag{12}$$

$$f2\colon X_W(i,j) = 1-(1-X'(i,j))^2. \tag{13}$$

To maintain good dot distribution characteristics of the binary ED algorithm, the white pixels of X'_W (the binary halftone result from X_W) are mapped to the corresponding positions of the X'_B image; that is, the pixel values of the corresponding positions on X'_B are replaced by the pixel values of the corresponding positions on X'_W. X'_B is the image



(a) Test color image



(b) Detected texture

Figure 3. Detected texture information.

after the pixels are replaced as follows:

$$X'_B(i,j) = \begin{cases} 255, & X'_W(i,j) = 255 \\ X_B(i,j), & X'_W(i,j) \neq 255. \end{cases} \tag{14}$$

Through such a substitution operation, the dot distribution characteristics of output X_B of the binary error algorithm are transmitted to X'_B.

Finally, the result of the multi-level ED is determined by X'_B, X'_W, and the input grayscale image $X(i,j)$. In the case of 2-bit (4-level) ED, the multi-level output can be represented as

$$Y(i,j) = \begin{cases} 0, & \text{if } X(i,j) \leq T \\ 85, & \text{if } X'_B(i,j) = 0 \text{ and } X'_W(i,j) = 0 \\ 170, & \text{if } X'_B(i,j) = 255 \text{ and } X'_W(i,j) = 0 \\ 170, & \text{if } X'_B(i,j) = 0 \text{ and } X'_W(i,j) = 255 \\ 255, & \text{if } X'_B(i,j) = 255 \text{ and } X'_W(i,j) = 255, \end{cases} \tag{15}$$

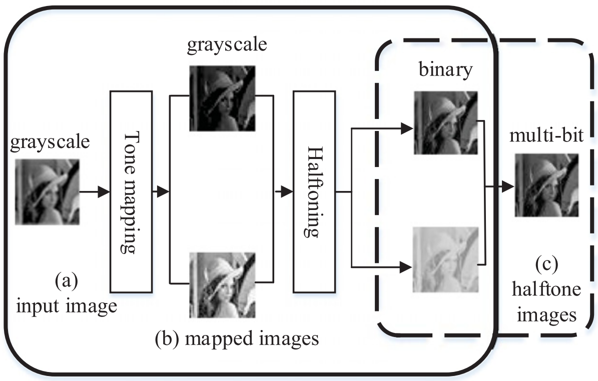


Figure 4. Process flow of multi-level ED.

where T denotes the threshold value. It is important to set pixels close to black in the original image (i.e., $Y(i, j) = 0$). The remaining three levels are determined by the black and white combination of the two nonlinearly transformed images.

Through the aforementioned transformation, pixel replacement, and pixel comparison operations, we obtain the final multi-level halftone image. This process only performs the most basic transformations in the field of image processing. Therefore, it will not significantly increase the original binary operation time of the halftoning algorithm.

3.3 *Experiment*

3.3.1 *Objective Evaluation*

We verified the physical performance of the proposed method by quantizing continuous-tone test images into halftone images and comparing the results to those of the conventional methods proposed by Floyd [3] and Shiau [4]. Figure 6 shows the test images used, and Figure 7 presents an example of quantized images, illustrating the effect of the proposed algorithm. Figs. 7(a) and 7(b) show a continuous gray image and the detected texture image, respectively, using our proposed algorithm. Figs. 7(c), 7(d), and 7(e) show the halftone image after halftoning using the algorithms of Floyd and Shiau and our ED algorithm, respectively. By comparing the halftone results, we can clearly observe that our algorithm can generate halftone images with good texture.

Similarity is a measure of resemblance between source and printed images as observed by humans. For this purpose, we must use an image-quality metric that considers the characteristics of the human visual system (HVS). In our objective evaluation, we selected the sparse feature fidelity (SFF) function [20] to compare the images and obtain a value between 0 and 1. This value represents the similarity between reference and distorted images. Thus, the SFF function indicates the extent of similarity. The SFF function reflects the chromatic properties of the HVS, and it is considerably effective for color-image-quality assessments. It is based on the color components of red–green–blue (RGB) and can detect color distortion in a perceptual manner. To achieve this purpose, we converted the digital halftone image from cyan–magenta–yellow–black to RGB before applying the SFF function. In this evaluation, the distorted image was replaced by a halftone image processed by a Gaussian filter to facilitate the experiment. The size of the Gaussian filter was 5×5, and the value of σ was set to 1.5.

Table I. SFF of the algorithms of Floyd and Shiau, and the proposed algorithm.

	(a)	(b)	(c)	(d)	(e)	(f)	Avg.
Floyd	0.861	0.857	0.852	0.845	0.832	0.820	0.844
Shiau	0.856	0.853	0.848	0.840	0.826	0.830	0.847
This work	0.856	0.858	0.855	0.848	0.837	0.831	0.848

Observing the halftone results in Fig. 7, we focus on the surface of the apple in each halftone image. Similarly to the real apple, the red skin of the apple in the original image is inlaid with many white spots. The areas of the spots on the apple surface in the original image are scattered and clear. After comparison, the closest to the distribution and sharpness of these spots is the halftone image generated by our proposed algorithm as shown in the upper right region of the apple surface in Figs. 7(c) and 7(d). We did not clearly observe the white spots. The reasons for this texture are the following: the white spots embedded in the apple skin and the surrounding red areas belong to the area of pixel value transitions; the Floyd and Shiau algorithms, which only changed the threshold value, transition in grayscale; the "contour" artifacts in the area affect the visual effect in the halftone image. Our algorithm has dealt with the problem of "contour" artifacts and can present such white spots similar to those in the original image in terms of quantity, size, and distribution. Therefore, although we cannot observe a significant difference in the "reflection" area in the images of oranges, our algorithm has advantage around this area.

To compare the objective data of the selected test images, we compared the SFF values of the Floyd and Shiau algorithms and the proposed algorithm. We used these three algorithms to process the six test images and then used the Gaussian filter to process the halftone images. Finally, we obtained the average value of the SFF as shown in Table I. From the table, we can see that the SFF value of the proposed algorithm is higher than that of the Floyd and Shiau algorithms (Fig. 6). We selected image regions from (a) to (f) that expressed different physical properties. For images (b)–(f), our algorithm performed best on objects such as plastics, glass, etc. These results showed that our halftone result is the most similar to the original image. However, from the result of (a), the performance of our algorithm was lower than that of Floyd, and our algorithm was inferior to the Floyd algorithm in representing the roughness. This is due to the limited edge information detected on a rough and single-color surface.

3.3.2 *Subjective Evaluation*

To subjectively evaluate the effectiveness of our algorithm, we compared its printing results with those of a raster image processor (RIP), Harlequin RIP®, developed by Global

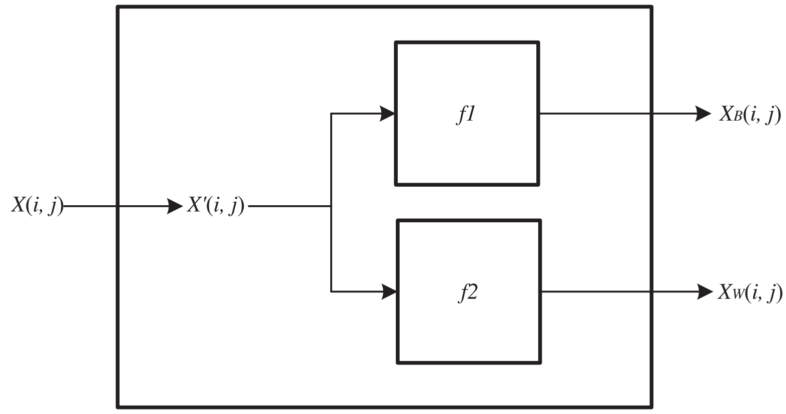


Figure 5. Tone mapping.

Figure 6. Test images used for objective evaluation.

Graphics. We printed the entire selected image with 600 dpi using a four-color printer.

Six pairs of test images were prepared for the evaluation as shown in Figure 8. The images were scanned using Brother DCP-J152N with 600 dpi. In each pair, one image was printed using the proposed method and the other using the RIP software. Figure 9 shows that each observer is required to score the left and right images after comparing them. The figure presents the scoring rules. There are 16 questions; each one regards the attributes of the printed image [21]. The total score of these questions is used as the standard for determining the quality of the printed image. For example, if the score of a certain test image is positive, this means that the quality of the left image is higher than that of the right image. Conversely, if the score of the test image is negative, the quality of the right image is higher than that of the left image. Thus, the higher the absolute value of the score, the higher the image quality. Finally, to ensure fairness in the experiment, we calculated the average score of seven observers for each test image and used it as the actual score.

Seven observers with normal vision participated in the experiment. They evaluated a pair of printed images under natural lighting conditions outdoors. The viewing distance was set as 20 cm. Table II shows the average score of each test image. As shown in the table, for all the test pairs, the proposed methods obtained higher scores from the observers.

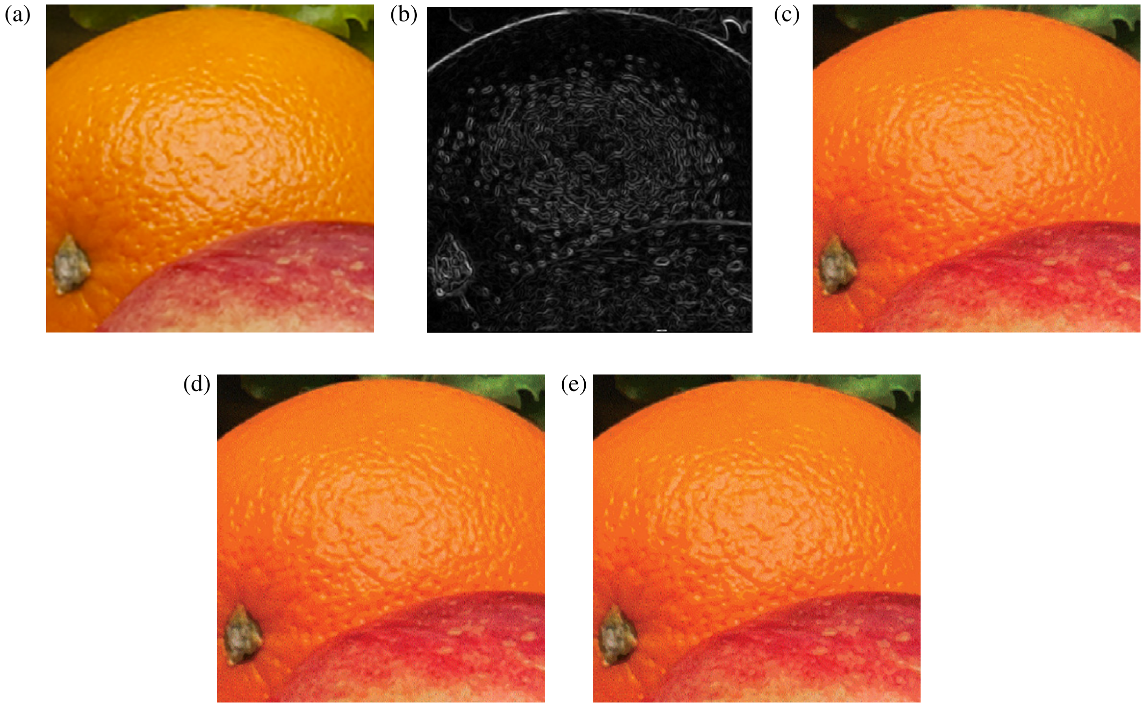


Figure 7. Experimental result of halftoning. (a) Original color image, (b) Texture information, (c) Floyd's ED result, (d) Shiau's ED result, (e) Proposed ED result.

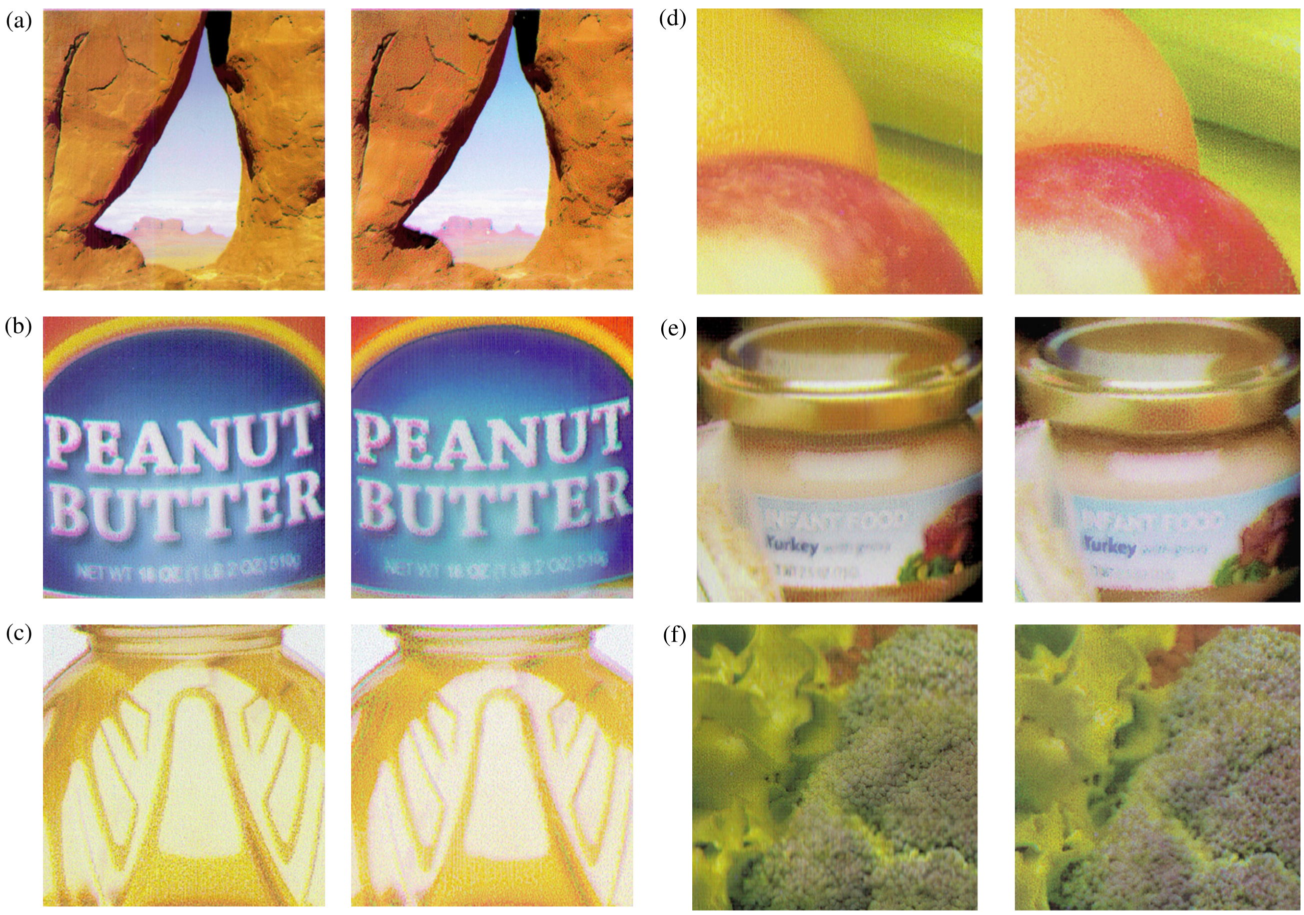


Figure 8. Printed images for subjective evaluation. (Left) Proposed algorithm. (Right) Current RIP software.

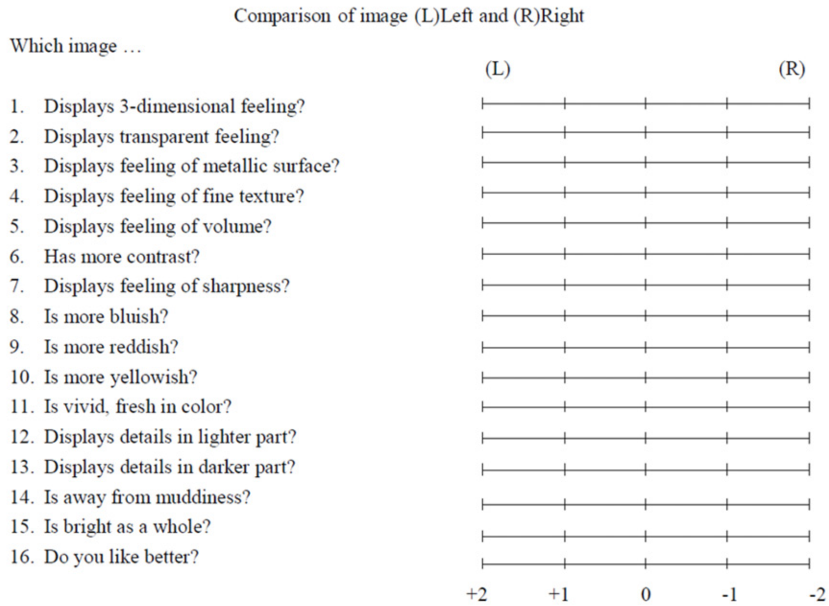


Figure 9. 16 Test questionnaire for subjective evaluation.

Table II. Average score of each test pair corresponding to seven observers.

	(a)	(b)	(c)	(d)	(e)	(f)
Score	+12.86	+10.71	+11.86	+9.86	+9.43	+10.14

3.3.3 *Physical Performance*

Computation time A comparison of the performance of several algorithms with regard to the average computation time for test images is provided as follows. The algorithms are presented in order from the fastest to the slowest.

$$\text{Pang} \gg \text{Floyd} > \text{ED used in this paper} > \text{Lee} \gg \text{Shi}.$$

Peak signal-to-noise ratio (PSNR) The performance of several algorithms with regard to the average PSNR for all test images is compared below in order from the highest to the lowest value.

$$\text{ED used in this paper} \simeq \text{Floyd} > \text{Pang} > \text{Lee} \simeq \text{Shi}.$$

Mean structural similarity (M-SSIM) The performance of the algorithms in terms of the average M-SSIM for all test images in order from the highest to the lowest value is as follows.

$$\text{Pang} > \text{ED used in this paper} \simeq \text{Floyd} \gg \text{Shi} > \text{Lee}.$$

4. CONCLUSION

We proposed a multi-level method that improves the texture representation of printed images through nonlinear transformation and binary texture-preserving ED. First, the nonlinear transformation was used to map the grayscale image to obtain two images with different brightness levels, process the images with binary halftone, and obtain the multi-value halftone result by synthesizing binary halftone results. Next, we used an edge-preserving ED algorithm, which improved the sharpness, reduced the loss of image quality caused by machine noise, and reduced the loss of white area caused by printer noise. We applied our methods to color packaging images from a website and confirmed their effectiveness. We also used a current RIP to print the halftone image and compared it with our algorithm printing. Consequently, we produced texture-aware images and reduced contouring artifacts in the transition region. Therefore, we obtained printed images with better texture presentation.

In future works, we will continue to explore more effective nonlinear transformation functions to further enhance the effect of nonlinearly transformed halftone images for presenting higher texture characteristics.

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