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Text-Enhanced Error Diffusion Using Multiplicative Parameters and Error Scaling Factor

Jae-Hyun Kwon, Chang-Hwan Son, Yang-Ho Cho and Yeong-Ho Ha▲
School of Electrical Engineering and Computer Science, Kyungpook National University,
1370 Sankyuk-dong, Buk-gu, Daegu 702-701, Korea
E-mail: yha@ee.knu.ac.kr

Abstract. *Text-enhanced error diffusion is proposed to sharpen text regions in complex documents, including natural images with a multifunctional printer. To enhance the sharpness of the text regions, the input image is segmented into text and background regions using the maximum gradient difference. Edge-enhanced error diffusion is then applied to the text regions to sharpen the text, while Floyd and Steinberg's error diffusion is applied to the background regions to obtain smooth dot patterns. However, this combination of algorithms can generate two kinds of artifact around the text regions: boundary and dot-elimination artifacts. Boundary artifacts are a series of dots distributed around text blocks, and this propagation error generated below a text line by the edge-enhanced error diffusion is largely diffused forward into the background region. Thus, to gradually decrease these propagation errors, a grayscale dilation operator is processed along the boundary of a text block, thereby creating a gradual dilated transition region. Edge-enhanced error diffusion using different multiplicative parameters is then applied to these regions. Meanwhile, dot-elimination artifacts are dot-disappearing phenomena occurring around high-frequency regions due to the characteristic of the edge-enhanced error diffusion to sharpen edge regions more. Thus, an error scaling factor is inserted in front of the error filter in the architecture of the edge-enhanced error diffusion to scale down the propagation errors. Experiments demonstrate that text readability is improved by increasing the sharpness of the text regions, and a less grainy appearance is simultaneously achieved compared with conventional edge-enhanced error diffusion in the background regions. © 2006 Society for Imaging Science and Technology.* [DOI: 10.2352/J.ImagingSci.Technol.(2006)50:5(437)]

INTRODUCTION

Multifunctional printers (MFP) have recently increased with the popularization of scanners, copiers, and printers. As such, a MFP is a printer device that includes a scanning mechanism, thereby providing convenience and a lower price to customers. However, MFPs invariably produce blurred documents as a result of their scanning mechanism. In particular, text or high-frequency regions are more degraded than background regions due to the halftone process. Therefore, it is necessary to sharpen the blurred text regions without amplifying any high-frequency noise. Two strategies have been used to solve these problems. First, text enhancement can be applied during the scanner process of the MFP. This approach sharpens text regions using a specific filter or contrast enhancement after text segmentation, thus resulting in more sharpened and better results.[1,2] However, it requires a lot of memory and computational complexity. Second, text enhancement can be applied during the halftone process of the MFP. This approach sharpens the text regions using edge-enhanced halftones after text segmentation. Various edge-enhanced algorithms have already been developed for grayscale images. Knox demonstrated that edge enhancement is an inherent characteristic of an error diffusion algorithm for texture patterns.[3] Similarly, Jarvis and Roberts and Stucki showed that a large filter-size sharpens an image more; however, the amount of sharpening may not be to the degree desired.[4–6] Thus, Eschbach and Knox proposed edge-enhanced error diffusion to control the degree of sharpness using a global parameter.[7] While a smaller value for the global parameter causes blurring with respect to the original grayscale image, large values cause sharpness. More recently, Lai and Chen proposed an edge-enhanced algorithm for color images,[8] where the RGB coordinate system is transformed into another coordinate system, for example YIQ or YCbCr, making the color components more independent in the new coordinate system. The error diffusion algorithm is then applied using different filters for each component of YCbCr. However, most of the above algorithms introduce noise around text regions in complex documents,[9] thereby breaking the shapes of the characters and lowering the readability of printed documents.

Accordingly, to reduce the noisy artifacts and increase the readability of characters, resulting in text-enhanced halftones, this paper proposes text-enhanced error diffusion using multiplicative parameters and an error scaling factor and combines text segmentation with text-enhanced error diffusion. Text segmentation can be achieved using the maximum gradient difference (MGD), which is the difference between the minimum and maximum gradient value calculated by applying a horizontal gradient operator to the input image. Thus, since it has already been empirically established that the MGD of a text region is larger than that of a background region, text regions can be extracted from an input image based on the value of the MGD.

Before halftoning, the boundaries of the text blocks are processed using a grayscale dilation operator, which is a kind of morphological processing and generally used to join broken segments in a binary image. In this study, grayscale dilation is used to create a gradual transition region around

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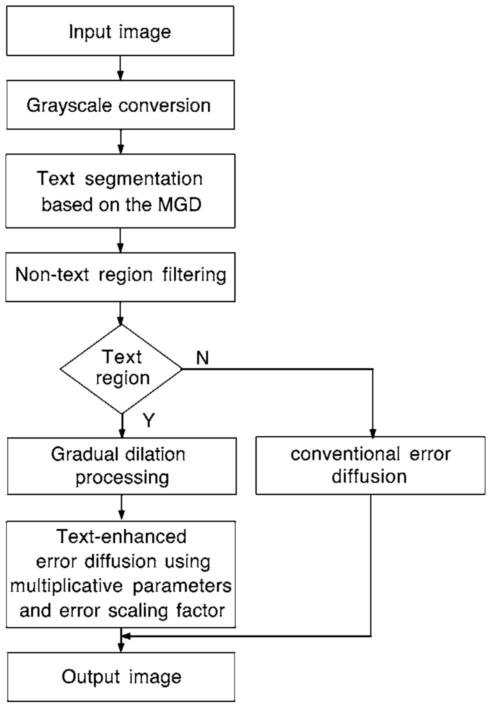


Figure 1. Flowchart of the proposed error diffusion with text enhancement.

the text blocks to reduce block artifacts. Thereafter, text-enhanced error diffusion using multiplicative parameters and an error scaling factor is performed. This algorithm is derived from Eschbach's edge-enhanced error diffusion and modified for text enhancement. Eschbach's edge-enhanced error diffusion has already been used for grayscale images, yet an unexpected color distortion occurs when it is applied to color images.[7] As such, conventional edge-enhanced error diffusion is suitably modified for color images. In addition, while conventional edge-enhanced error diffusion uses a fixed and single multiplicative parameter, the proposed method uses various multiplicative parameters to reduce block artifacts, plus an error scaling factor is added to the architecture of the edge-enhanced error diffusion to reduce dot elimination artifacts.

THE OVERVIEW OF THE PROPOSED TEXT-ENHANCED ERROR DIFFUSION

Figure 1 shows a flowchart of the proposed text-enhanced error diffusion. The input image is converted into a grayscale image using only the luminance information in YCbCr space. Text segmentation based on the MGD is then performed on the grayscale image to extract the potential text areas from the grayscale image. However, nontext fragments such as high-frequency components are still included in the potential text areas. Therefore, nontext region filtering is applied to potential text areas for noise reduction. In addition, a gradual dilation method is utilized along the text blocks to reduce the boundary artifacts generated by two kinds of halftoning algorithms. Thereafter, conventional error diffusion is used on the background regions, while text-enhanced error diffusion using multiplicative parameters and an error scaling factor is applied to the text regions. As such, text enhancement can be achieved without visually objectionable artifacts.

GRAYSCALE CONVERSION

In general, it has been found that the intensity or color of text remains almost constant in complex documents. Thus, text detection using a grayscale-converted image is more efficient than using every component of each color channel. Grayscale image can be variously calculated according to the selection of the color space, for example, HSI, YCbCr, and CIELAB. HSI color space is the simplest method to acquire the intensity value from color image, yet consider how each RGB channel can have an influence on making the grayscale like YCbCr color space. By contrast, the CIELAB color space includes nonlinear computations and is not suitable for hardware implementation even though color difference is uniformly provided. Therefore, the YCbCr color space is used to make grayscale image for a simple implementation

$$Y = 0.299R + 0.587G + 0.114B, \tag{1}$$

where each RGB value is normalized to [0-1] and Y is a grayscale image. If the input is a grayscale image, this process is not necessary and jumps directly to the next step.

TEXT SEGMENTATION BASED ON THE MAXIMUM GRADIENT DIFFERENCE

Text segmentation based on the MGD is essentially derived from the method of Wong and Chen who developed a video text-extraction algorithm that uses fast filtering based on the MGD for text-region identification.[10] This algorithm is composed of three steps; mask convolution, MGD-calculation, and MGD-threshold. First, mask convolution step convolves a horizontal mask with a grayscale image along the scan line to obtain the gradient value of the grayscale image based on the assumption that text characters form a regular texture, including vertical strokes aligned horizontally

$$\mathrm{Grad}(x,y) = \sum_{y=1}^{H} \sum_{x=1}^{W} \sum_{i=-1}^{1} w(i) Y(x+i,y), \tag{2}$$

where $w(i)$ is a horizontal mask and $[-1\ 0\ 1]$ is used within the limit of using only 1-line buffer in the MFP to realize hardware implementation and reduce the memory. (x,y) is a spatial coordinate and (H,W) represents the height and width of the grayscale image. After acquiring the gradient value, MGD is calculated by subtracting the minimum gradient value from the maximum gradient value within a local window to separate the text region from the grayscale image

$$\mathrm{MinGradient} = \min\{\mathrm{Grad}(x-n/2-1,y), \ldots, \mathrm{Grad}(x,y), \ldots, \mathrm{Grad}(x+n/2,y)\}, \tag{3}$$

$$\mathrm{MaxGradient} = \max\{\mathrm{Grad}(x-n/2-1,y), \ldots, \mathrm{Grad}(x,y), \ldots, \mathrm{Grad}(x+n/2,y)\},$$

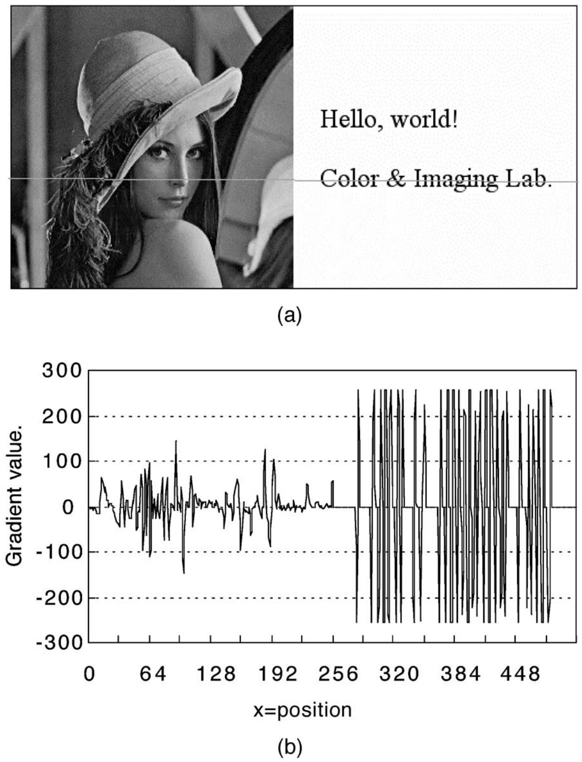


Figure 2. Horizontal gradient: (a) input image and (b) gradient profile for scan line 159.

$$\mathrm{MGD}(x,y) = \mathrm{MaxGradient} - \mathrm{MinGradient},$$

where MGD is the maximum gradient difference and (MaxGradient, MinGradient) is the maximum and minimum gradient value within a local window of size $n \times 1$ centered at the current pixel position (x,y). Both min and max are functions that are used to find the minimum and maximum value of the input elements. The window size (n) should be larger than the stroke width of the largest text character being detected. In this study, $n=15$ was selected as appropriate for small-size characters in books or magazines. MGD-threshold step maps the MGD values into 0 or 255 to extract the potential text regions from the grayscale image. If MGD is above a threshold, the pixel is considered to be a text element for the potential text regions. For simplicity, 58.64 is given as a fixed threshold value, which is the average of the threshold values obtained by the application of Otsu's algorithm to dozens of MGD images.[11] These text elements create the text line segments, which extract the potential text regions from background.

Figure 2(b) shows the gradient profile of the 159th scan line from the test image with an image size of 512×256, in Fig. 2(a). Note that the text area shows a large gradient magnitude compared with the Lena image area. Using the gradient values, the MGD is then calculated and evaluated to detect text line segments from the horizontal scan lines within an n-pixel local window. Since the MGD values between $x=280$ and $x=480$ are very large compared with the MGD values between $x=0$ and $x=280$ in Fig. 2(b), in other words, the MGD values of text region are greater than the MGD values of background, potential text regions can be detected in an input image by analyzing the MGD values. These MGD values are mapped into 0 or 255, thereby creating a binary MGD image by threshold processing.

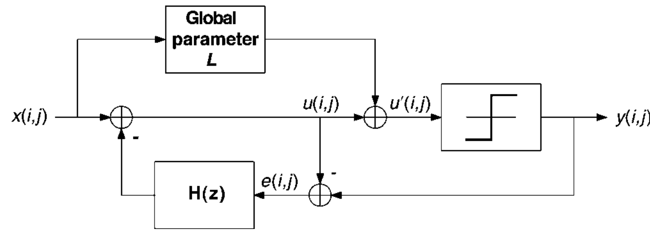


Figure 3. Conventional edge-enhanced error diffusion.

NONTEXT REGION FILTERING

Postprocessing is unavoidable, as high-frequency regions and vertical lines with large MGD, which are not part of the text region, can be detected in the binary MGD image. If the window is $n \times 1$, then successive pixels smaller than $2n$ along with horizontal scan lines are eliminated in the binary MGD image. Morphological postprocessing, including dilation and erosion, is then used to reduce noise and produce better segmentation results.[10] In the experiments, erosion was applied twice and dilation then used three times to filter any noise and non-text areas from the binary MGD image.

THE DECISION OF THE GLOBAL PARAMETER VALUE IN CONVENTIONAL EDGE-ENHANCED ERROR DIFFUSION FOR COLOR IMAGE

Conventional edge-enhanced error diffusion was previously developed by Eschbach and Knox,[7] and has been used to increase the edge enhancement for grayscale images. The key feature of this method is the introduction of an input-dependent threshold into the process, which can be done by multiplying the input value by global parameter (L) as shown in Fig. 3. The global parameter, which is a constant set by the user at the beginning of the process, directly controls the image dependence of the threshold and influences the amount of edge enhancement that will be the output image. In Fig. 3, the updated input is

$$u(i,j) = x(i,j) - \sum_{m.n} h(i-m,j-n)e(i-m,j-n), \qquad (4)$$

where $x(i,j)$, $h(i,j)$, and $e(i,j)$ represent the input pixel, error filter, and propagation error, respectively. The modified input value is

$$u'(i,j) = u(i,j) + Lx(i,j) = (L+1)x(i,j) - \sum_{m,n} h(i-m,j-n)e(i-m,j-n) \qquad (5)$$

and the output value is

$$y(i,j) = Q[u'(i,j)], \qquad (6)$$

where $Q(\cdot)$ is the quantization process. The updated input value (u) is modulated to modified input value (u') before

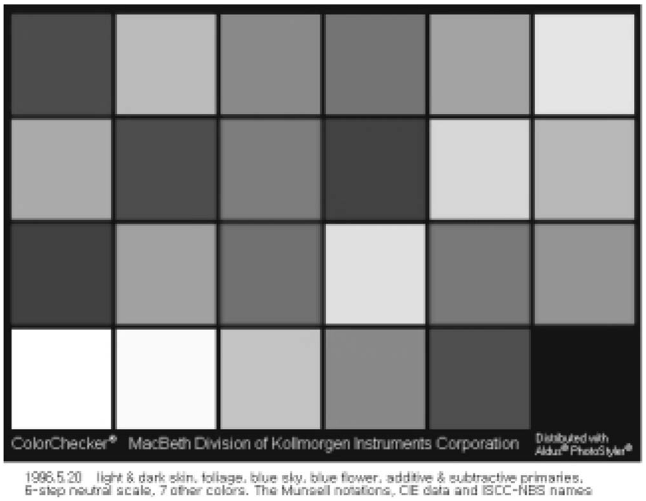


Figure 4. Macbeth ColorChecker.

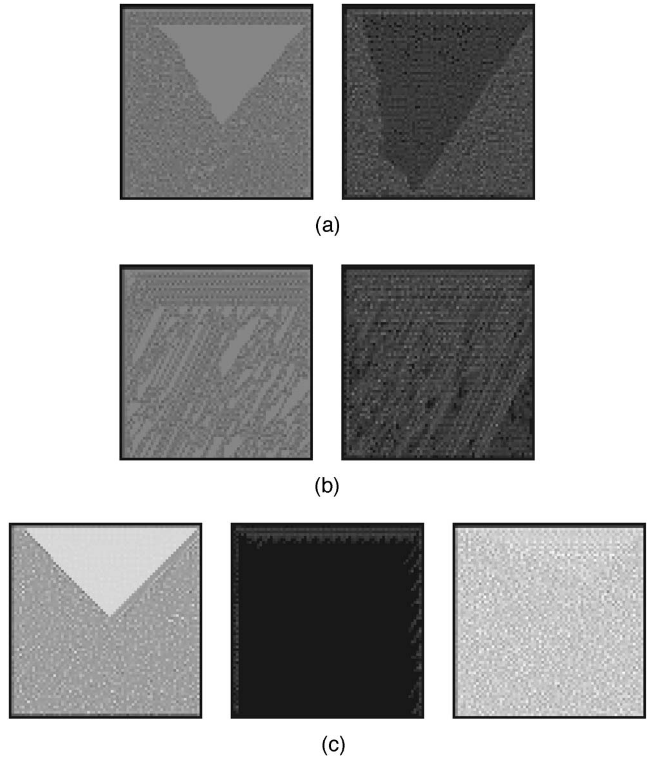


Figure 5. Unstable patches: (a) $L=1.4$, (b) $L=1.5$, and (c) $L=1.6$.

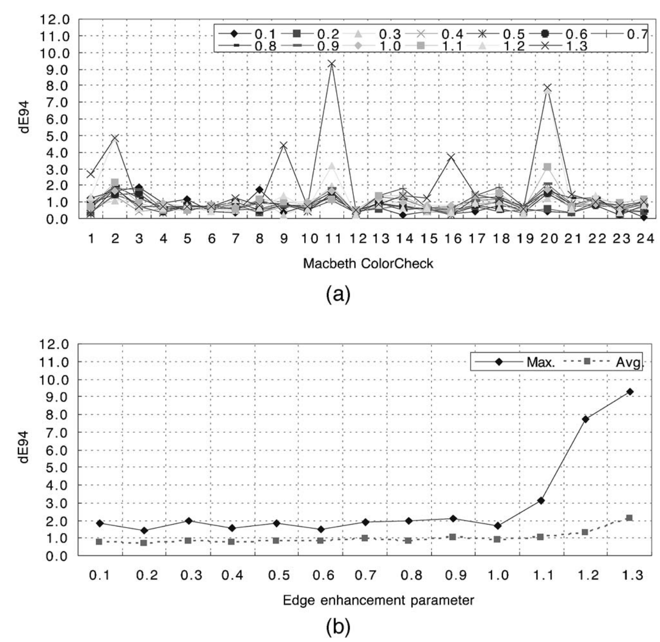


Figure 6. CIE94: (a) ΔE^*_{94} for Macbeth ColorChecker and (b) average and maximum ΔE^*_{94} according to the edge-enhancement parameters.

the quantization process by adding the multiplied input value (Lx). If $L=0$, the algorithm reduces Floyd and Steinberg's error diffusion. For large values of L, the modified input value is more sensitive to image details due to the addition of high multiplied input value, which enhances the sharpness of image more. For small values of L, thresholding decision becomes less sensitive to edge detail as low multiplied input value is included before the quantization process, and the image is less sharp.

By the way, edge-enhanced error diffusion, mentioned above, unfortunately generates unexpected colors in smooth regions when applied to the color images. As the value of L increases, the edge enhancement is more definite, yet this causes more color distortion. In other words, it can cause unstable dot pattern and color difference. Thus, it is necessary to achieve a compromise between edge enhancement and color distortion. To investigate the color distortion generated by the increment of L, the Macbeth chart in Fig. 4 is repetitively printed with increasing the value of the global parameter by 0.1 increments. From the visual evaluation, the dot patterns of the halftone patches in the Macbeth chart are considerably broken up and unstable when the global parameter value reaches 1.4 as shown in Figs. 5(a)–5(c). As such, the global parameter value should not be larger than 1.3 to prevent unstable dot distribution.

Under this restriction, the global parameter value can be reasonably decided by examining the color difference of the Macbeth chart. The CIE94 as color difference metric was calculated based on the average $L^*a^*b^*$ values, measured five times.[12] For the 24 patches of the Macbeth chart, dE^*_{94} is shown in Fig. 6(a) according to the global parameter value between 0.1 and 1.3 in 0.1 increments. Note that a few patches showed a large error with a high global parameter value. The reason is that certain pixels distributed near the threshold of quantizaton are highly amplified. Thus, most of the pixels exceed the threshold of quantization, resulting in a large color difference. Figure 6(b) shows the average and maximum dE^*_{94}, including an abrupt increase in the maximum color difference starting at $L=1.1$. Therefore, L is determined as 1.0 to satisfy the conditions that average color difference is less than 1.0 and the maximum color difference is less than 2.0.

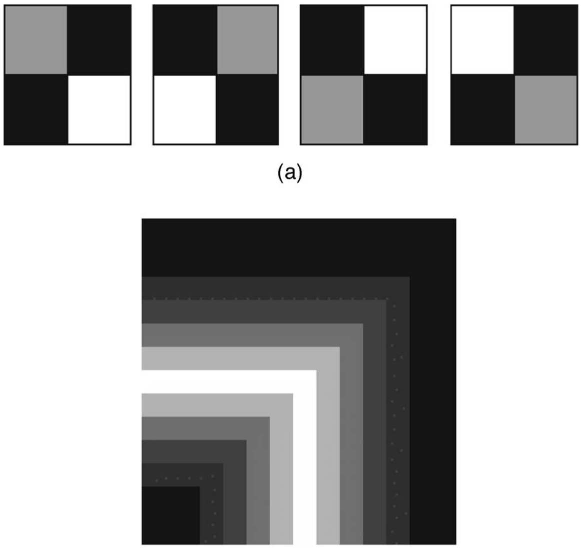


Figure 7. Gradual dilation method: (a) structure element and (b) result of the gradual dilation.

THE PROPOSED TEXT-ENHANCED ERROR DIFFUSION USING MULTIPLICATIVE PARAMETERS AND ERROR SCALING FACTOR

Conventional error diffusion generates coarse dot patterns compared with Floyd and Steinberg's error diffusion due to the use of global parameter.[7] Therefore, after text segmentation, Floyd and Steinberg's error diffusion is applied to background regions to obtain a smooth dot pattern, while conventional edge-enhanced error diffusion is applied to sharpen the text regions. However, two kinds of artifacts are generated: boundary and dot-elimination artifacts. First, boundary artifacts are a series of dots distributed around a text block, which is resulted from the combination of the two kinds of halftone algorithms. Below the text line, propagation errors resulting from edge-enhanced error diffusion are largely diffused forward into the background region. As a result, the uniformity of dot distributions is broken up and a series of dot distributions are generated below text line.

To solve this problem, a grayscale dilation method is applied to the boundary of the text blocks before the halftone process to decrease these propagation errors gradually. Grayscale dilation is a kind of morphological process and used to create a gradual transition region around the text block. For the binary MGD images extracted from text segmentation, grayscale dilation is executed as follows:

$$\mathrm{GDTR} = \bigcup_{j=1}^{n} \left(\bigcup_{k=1}^{4} A \oplus B^{k}_{g_{p_j}, g_{t_j}} \right), \tag{7}$$

where $\oplus$ is grayscale dilation. The GDTR is a result of grayscale dilation and represents the gradually dilated transition regions around the text blocks. n is iteration step and is equivalent to the number of gray level used in the GDTR. A is the binary MGD image, $B^{k}_{g_{p_j}, g_{t_j}}$ is the k types of the 2×2 structure elements, $\cup$ is the union. Each structure element consists of three types of elements, i.e., black, gray, and white as shown in Fig. 7(a). The gray element corresponds to the pixel (p_j) being changed into a part of the GDTR and the white element corresponds to the target pixel (t_j) belongs to the initial text block or a portion of the GDTR, while the black elements are irrelevant terms

$$g_{t_j} = \begin{cases} 1 & \text{if } j = 1 \\ g_{p_{j-1}} & \text{if } 1 < j \leqslant n, \end{cases} \tag{8}$$

$$g_{p_j} < g_{p_{j-1}}, \tag{9}$$

$$0 \leqslant g_{p_j} \leqslant 1. \tag{10}$$

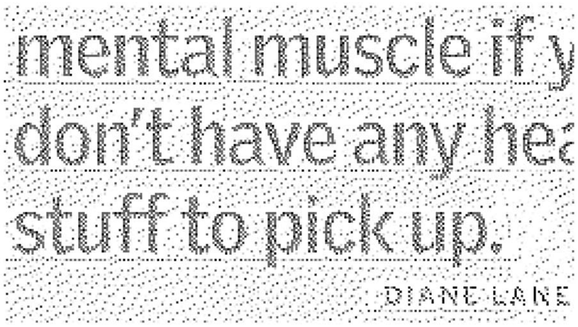
Grayscale dilation begins at $j=1$ and the initial target pixel with the graylevel (g_{t_1}) is regarded as the text block of the binary image. If the white element is placed on the initial target pixel, the graylevel g_{p_1} less than 1 is assigned to the current pixel corresponding to the gray element, which is also substituted into the graylevel (g_{t_2}) of the next target pixel as in Eq. (8). After this process is equally applied to the four types of structure element, union is performed and jumps to the next step. At the next step $j=2$, the graylevel of the gray element is given by g_{p_2} less than previously processed g_{p_1} satisfying the Eq. (9) if the white element is placed on the target pixel with the graylevel g_{t_2}. This kind of procedure is repetitively executed until j reaches the iteration number, making the gradual decreasing graylevel ($g_{p_1}, g_{p_2}, \ldots, g_{p_n}$) between the text region and the background.

Figure 7(b) shows a sample result of the gradual dilation. If the text region is white and the background is black, the expanded region will have gradually darkening gray levels, thereby creating a GDTR between the text and the background. For these regions, the value of global parameter is differently used in the architecture of edge-enhanced error diffusion to decrease the propagation error gradual. Table I shows the values of the global parameter according to the graylevel of the GDTR. The values in Table I were chosen empirically and they have a multiplicative relationship, thereby calling them multiplicative parameter to discriminate the global parameter. Also, it is found that the five classified parts for the graylevel are sufficient to reduce boundary artifacts. Figure 8(a) shows an example of the boundary artifact and Fig. 8(b) shows the result of the edge-enhanced error diffusion with multiplicative parameter and the grayscale dilation method. In Fig. 8(b), the boundary artifacts are effectively removed by applying the multiplicative parameter for the GDTR.

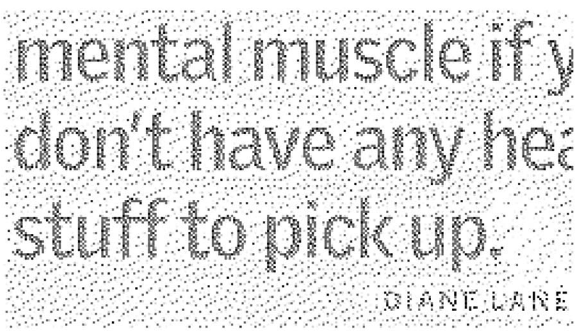
Second, dot-elimination artifacts are a dot-disappearing phenomenon around high-frequency regions due to the characteristic of the built-in edge sharpness in edge-enhanced error diffusion. Therefore, the proposed text enhancement algorithm uses an error scaling factor in addition to the multiplicative parameter, as shown by the block dia-

Table I. Edge enhancement parameters according to the GDTR values.

GDTR	1–31	32–63	64–127	128–191	192–255
L	0.125	0.25	0.5	0.75	1.0



(a)



(b)

Figure 8. A comparison of halftone results: (a) without gradual dilation and (b) with gradual dilation and multiplicative parameter.

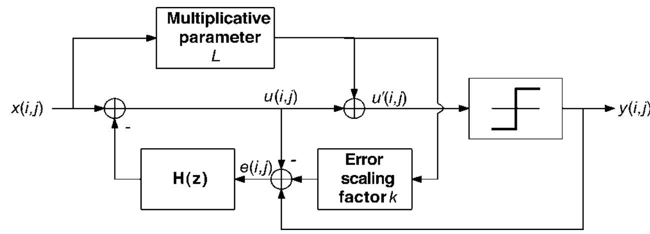


Figure 9. Block diagram of the proposed text-enhanced error diffusion.

gram in Fig. 9. The propagation error of the proposed method is modified as follows:

$$e(i,j) = y(i,j) - u(i,j) + kLx(i,j), \tag{11}$$

where k is the error scaling factor to scale down the multiplied input value (Lx). For the high frequency regions, propagation errors are largely diffused to the neighborhood pixels as the multiplied input value is added to the input value before the quantization process. As a result, most of the pixel values exceed the quantization level and the dot-disappearing artifacts are generated around high-frequency regions. Thus, it is necessary to reduce these propagation errors by considering the multiplied input value. Since the multiplied input value is generally large and cannot be applied directly, it should be scaled down in proportion with the error scaling factor in front of the error filter. A point to be considered is that the use of the error scaling factor creates the intensity variation in the smooth regions. Thus, the value of the error scaling factor is decided by examining the effect of reducing both dot-elimination artifacts and intensity variation for various gray patches as in Fig. 10(a). From the repetitive experiment, k is empirically selected as 0.05, satisfying the intensity variation less than 3-level for the 8-bit input image.

Figures 10(b)–10(d) shows the halftoned results of Floyd and Steinberg's error diffusion, conventional edge-enhanced error diffusion with $L=1.0$, and the proposed method for the (0.3–0.7) step input as shown in Fig. 10(a). From these figures, it is known that conventional edge-enhanced error diffusion gives a better performance among the three types of halftoning algorithms for edge enhancement and Floyd's error diffusion has a built-in edge sharpness characteristic. To evaluate a degree of sharpness quantitatively, the average output gray level is examined in Figs. 10(e)–10(h) for the 4096 line. The degree of sharpness is evaluated by the difference between the overshot graylevel and the undershot graylevel at position$=0$. If the difference value is significant, it can be said that used halftoning algorithm provides better sharpness. From this point of view, the proposed method yields a sharpness performance as good as conventional edge-enhanced error diffusion and has no effect of edge enhancement though of the addition of error scaling factor.

By contrast, Figs. 11(b)–11(d) show the halftoned results for the (0.05–0.95) step input with abrupt variation in intensity. Dot-disappearing artifacts come into existence at the border of different graylevels by the large propagation error diffused from the neighbor pixel. To investigate the dot-disappearing artifact quantitatively, the average output graylevel is examined in Figs. 11(e)–11(h) for the 4096 line and the degree of dot-disappearing artifact can be evaluated by analyzing the width of flat level at position$=0$. It can be seen that the width of the flat level in Fig. 11(h) is smaller than that of Fig. 11(g). Therefore, the error scaling factor of the proposed method can significantly reduce the dot-disappearing artifact, as compared with conventional edge-enhancement error diffusion using only global parameter. In addition, more sharpness can be achieved in Fig. 11(d) than Floyd and Steinberg's error diffusion. As such, the proposed text-enhanced error diffusion can obtain sharper images and the use of the error scaling factor did not have an effect on

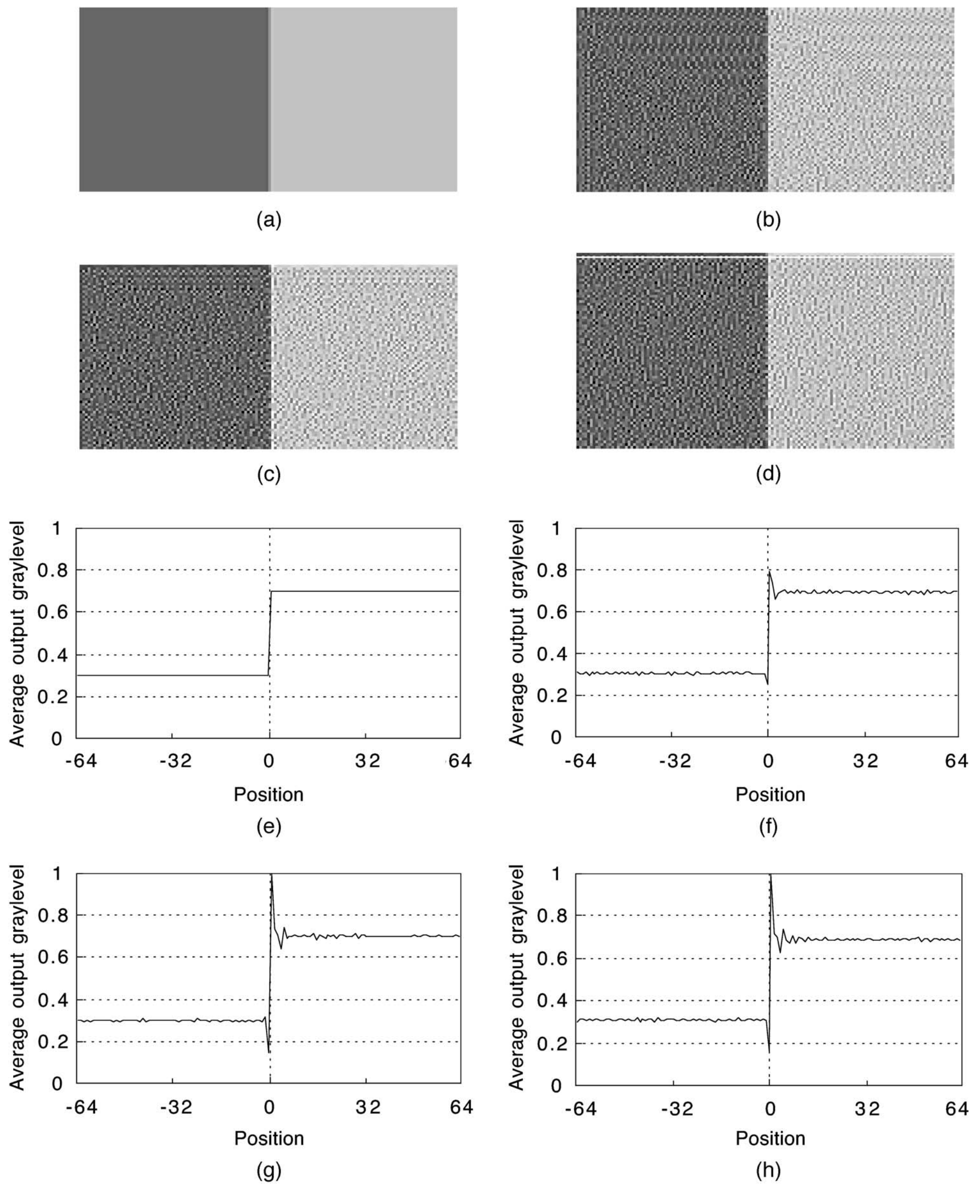


Figure 10. (0.3–0.7) Step response: (a) input image, (b) Floyd-Steinberg error diffusion, (c) edge-enhanced error diffusion, (d) proposed text-enhanced error diffusion, and (e)–(h) average output graylevel.

the amount of edge enhancement, i.e., the peak-to-peak values for each step response.

EXPERIMENTAL RESULTS OF TEXT SEGMENTATION

Figure 12 shows the results of the text segmentation process. The input color image in Fig. 12(a) includes both natural image and text images that can be used to evaluate the sharpness and dot distribution of complex documents. Due to problems with copyright, the ISO standard image is used as a natural image and is compounded with text images scanned by using an HP Scanjet 7400c at 400 dpi. Figure 12(b) shows the gradient results after mask convolution. Using this gradient information, the text segments were then detected and merged based on the MGD values, as shown in Fig. 12(c). Due to the simple MGD method, the edge component in a natural image can be extracted with text region, yet most of the text regions can be effectively detected for three kinds of languages of different sizes. Practically, the matters of memory and computation take precedence of accuracy of the text segmentation for the manufacturing of MFP. Figure 12(d) shows the thresholded binary image. In these experiments, 50 is used as a predefined threshold value for documents with a light background and dark-colored text. Next, nontext region filtering, consisting of erosion and dilation, was performed to eliminate isolated segments and noise. The results are shown in Fig. 12(e). Thereafter, gradual dilation was applied to the text regions to make the GDTR with various graylevels around the text blocks in Fig. 12(f). Although a few nontext regions remained, the visual artifacts generated did not have much of an effect on the halftones of the image area.

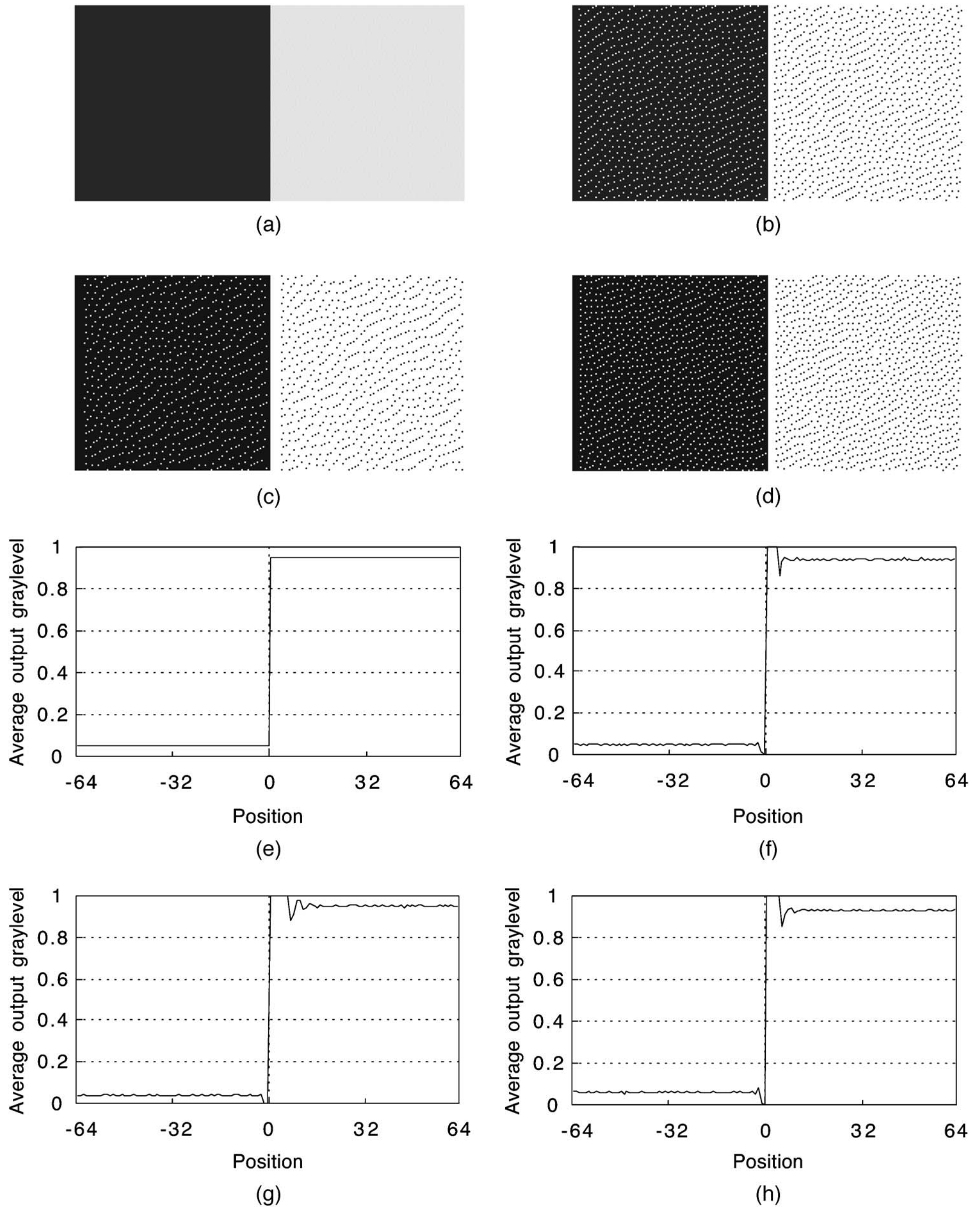


Figure 11. (0.05–0.95) Step response: (a) input image, (b) Floyd-Steinberg error diffusion, (c) edge-enhanced error diffusion, (d) proposed text-enhanced error diffusion, and (e)–(h) average output graylevel.

A COMPARISON OF THE HALFTONE RESULTS

The performance of the proposed algorithm and four other halftoning algorithms were compared. Figures 13(a)–13(e) show the scanned results of Floyd and Steinberg's error diffusion, Jarvis' error diffusion,[4] Eschbach and Knox's edge-enhanced error diffusion,[7] Lai and Chen's error diffusion using different error filters,[8] and the proposed algorithm. For the text regions in Fig. 13(a), the sharpness of the text regions was lower in Figs. 13(b)–13(e), although smooth dot patterns were reproduced in parts of fruits, color chart, and high frequency. Nonetheless, the results in Figs. 13(b)–13(d) showed that the sharpness of the text and high-frequency regions were more enhanced and the degree of sharpness was similar. Yet, dot-elimination artifacts were still observed in the boundaries of the detected text blocks and high-frequency regions, making the dot distribution nonuniform. In addition, the dot patterns were coarser than Floyd and Steinberg's error diffusion in the background regions. From Figs. 13(b) and 13(d), a large filter size was found to sharpen the image more, even when different error filters (Jarvis and Stucki filter[4,5]) were applied to the YCbCr space, as in Fig. 13(d).[8] In Fig. 13(e), dot-elimination artifacts were more effectively removed by the inclusion of the error scaling factor below the text lines, which generated a homogeneous dot pattern below the text lines and increased the quality of the resulting image. Furthermore, the dot patterns were smoother than in Figs. 13(b)–13(d), and the sharpness of the text regions was as good as in Figs. 13(b)–13(d) when

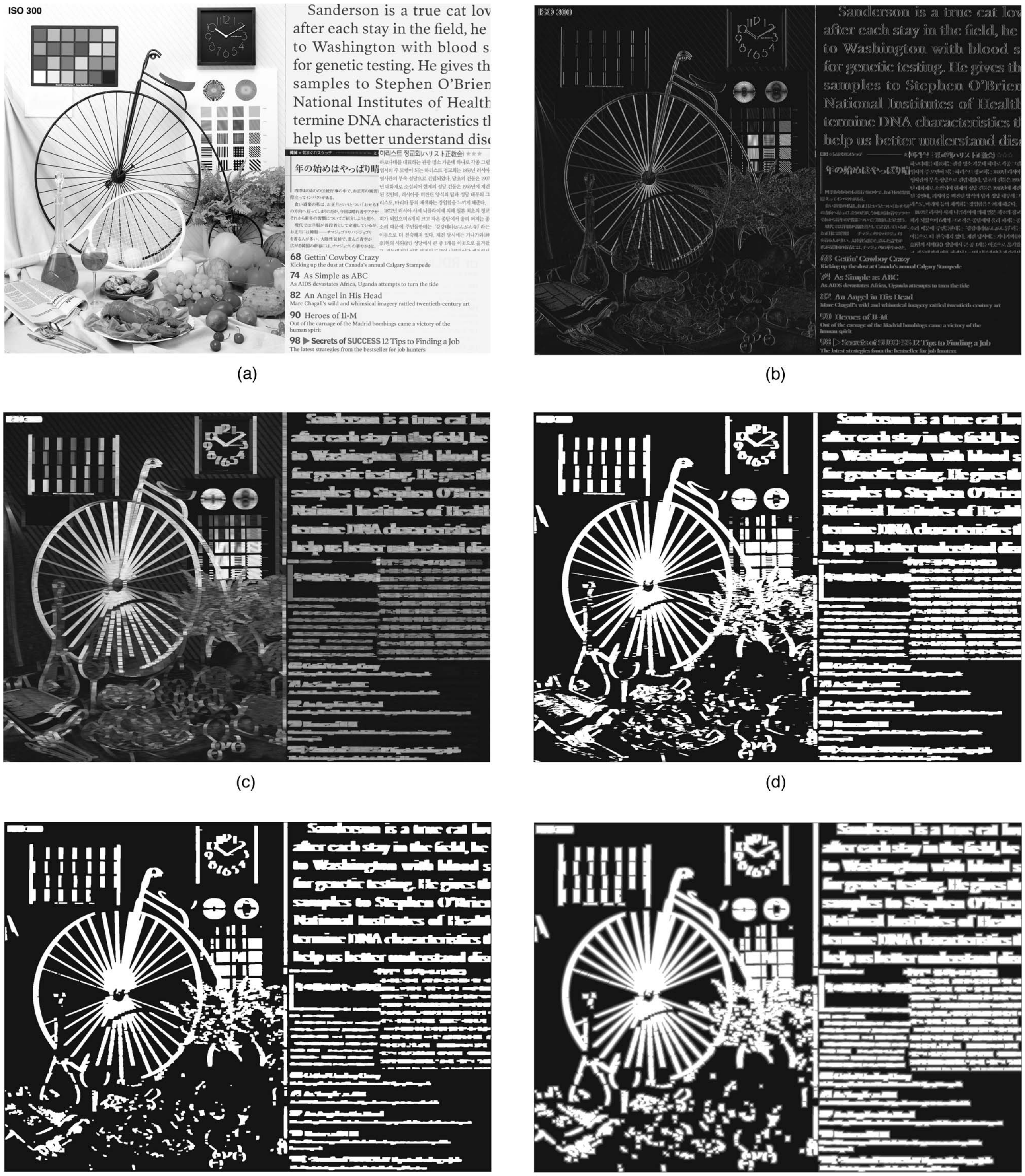
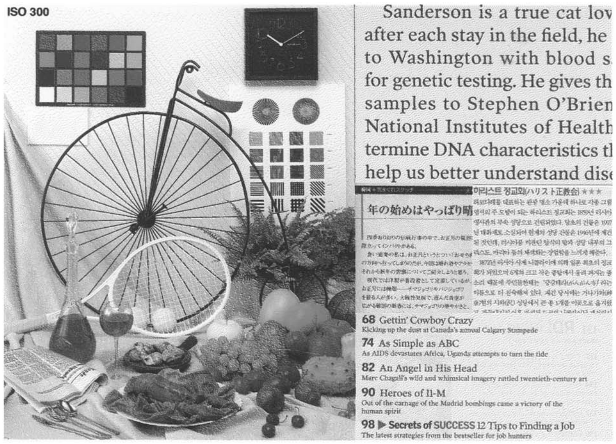


Figure 12. The results of the text segmentation: (a) input image, (b) gradient, (c) MGD, (d) thresholded MGD, (e) filtered image, and (f) GDTR.

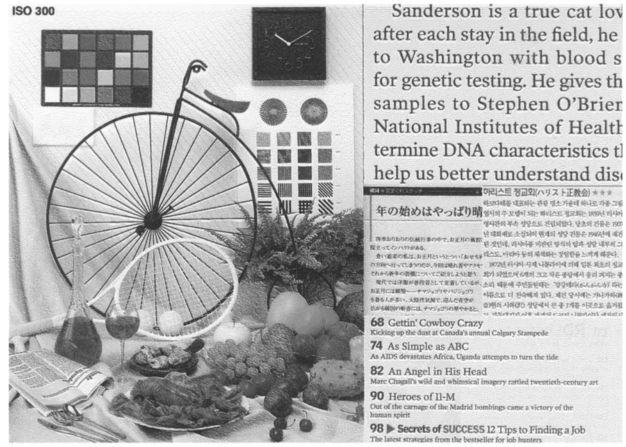
using multiplicative parameters according to the GDTRs. Consequently, from these results, the proposed method demonstrated that it could sharpen text regions without dot-elimination artifacts and generate smooth dot patterns for the background regions.

CONCLUSION

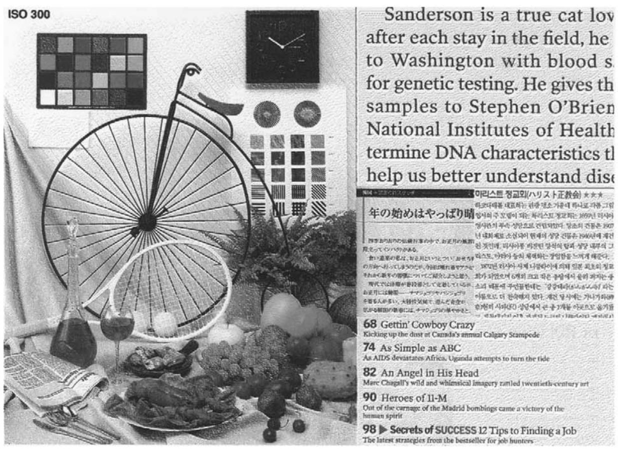
Text-enhanced error diffusion using multiplicative parameters and an error scaling factor is proposed to improve the sharpness of characters in complex documents. As such, be-



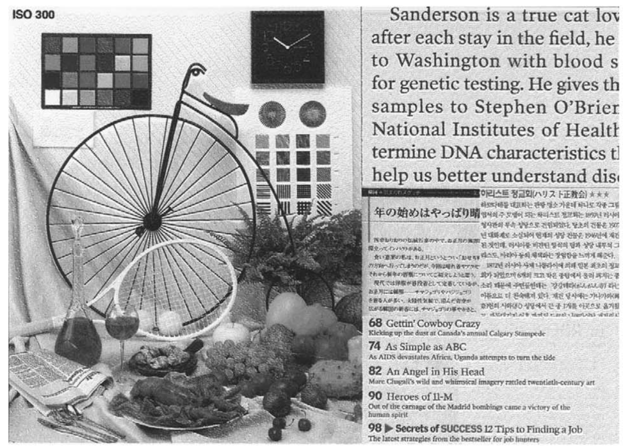
(a)



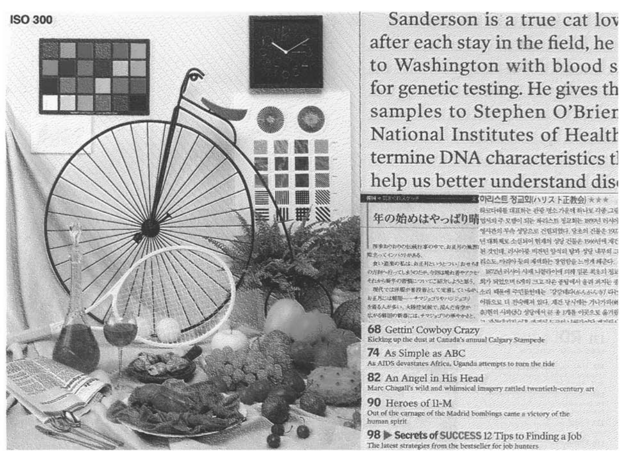
(b)



(c)



(d)



(e)

Figure 13. Comparison of the halftone results: (a) Floyd and Steinberg's error diffusion, (b) Jarvis's error diffusion, (c) Eschbach and Knox'sedgeenhanced error diffusion, (d) edge-enhanced error diffusion using different filters, and (e) proposed text-enhanced error diffusion using the multiplicative parameters and error scaling factor.

fore halftoning, simple text segmentation using the MGD is conducted to extract text regions. Edge-enhanced error diffusion is then applied to the text regions, while Floyd and Steinberg's error diffusion is applied to the background regions. The boundary artifacts that are unavoidably generated around the text regions when using two kinds of halftone algorithms are then reduced by edge-enhanced error diffusion with gradual increase in edge-enhancement parameters.

An error scaling factor is also inserted in the architecture of the edge-enhanced error diffusion to reduce dot-elimination artifacts. Experiments showed that the proposed method generated smoother dot patterns in the background regions than conventional edge-enhanced error diffusion, plus sharper results were produced in the text regions than by using Floyd and Steinberg's error diffusion. In particular, dot-elimination artifacts were effectively removed below text lines and homogeneous dot patterns generated around text blocks. The proposed method is also applicable to other error diffusion algorithms with different error filters and only requires small memory capacity and moderate computational costs, making it applicable to printers and MFPs.

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