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ORIGINAL ARTICLE

Structure-aware error-diffusion approach using entropy-constrained threshold modulation

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Abstract Error diffusion is known as a commonly used digital halftoning technique. We present a novel and efficient error-diffusion algorithm which is capable of preserving appreciable structures and tones with blue-noise property. According to the theoretical analysis of threshold modulation, the extraction of the high-frequency image contents is helpful to preserve human vision-sensitive textures. The pixel intensity's influence on the structural distortion is observed based on a key statistic phenomenon. This effect leads to the non-uniform conservation of diversiform detail contents. To alleviate this influence, an entropy is introduced to measure the intensity's impact and adaptively constrain the threshold-modulation strength. Compared with the existing edge-enhancement halftoning, our entropy-based method does not suffer from the failure to detect weak edges or improper emphasis of details. On the other hand, this structural improvement enables the modification of error-diffusion coefficients to eliminate visually harmful tonal artifacts, which results in the seamless integration with the best tone-aware techniques (Ostromoukhov in Proceedings of ACM SIGGRAPH, SIGGRAPH '01, pp 567–572, 2001, Zhou and Fang in ACM Trans Graph (TOG) 22(3):437–444, 2003). Comparisons with the state-of-the-art structure-preserving error diffusions (Chang et al. in ACM Trans Graph (TOG) 28(5): 162:1–162:8, 2009, Li and Mould in Forum 29(2):273–280, 2010) indicate that our methods can achieve better structural similarity with better tone consistency. Our performance is one order of magnitude faster than (Chang et al. in ACM Trans Graph (TOG) 28(5): 162:1–162:8, 2009, Li and Mould in Forum 29(2): 273–280, 2010) while ensuring higher visual quality on typical images. Due to low computational overhead and high halftone quality, the proposed methods in this paper can be widely applicable in many practical applications.

Keywords Error diffusion · Entropy · Threshold modulation · MSSIM

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1 Introduction

Error diffusion [7] is a well-known halftone method. It converts a continuous tone image into a binary tone image that can appear visually similar with the original input image when observed from a certain distance away. The principle of this algorithm is to compensate the quantization errors by distributing them on to the neighboring pixels of the input image [26]. Compared with other halftoning techniques, the main advantages of error diffusion are its simplicity and favorable visual quality. And it is applied widely in many actual applications. The previous improvements on its halftoning quality mainly focus on the following two aspects.

One is how to minimize various visible artifacts and maintain tone consistency. According to the dissimilarities of processing modes, the promotions can be classified into two groups: one is the alteration of the processing path such as the usage of serpentine path [18,21,26] or space-filling curves [2,23,25], instead of scanlines; and the other is the adjustment of the diffusion range and diffusion coefficients [18,26]. The algorithms described in [18,26] show the best results among all the tone-aware methods above. But these methods do not attempt to preserve the structural features, which causes serious loss of many important details (see [5,19]).

The other is how to convey the characteristic appearance of textured or structural regions. Note that many early halftoning algorithms are hard to convey the internal structural features of original images, a number of researchers employed edge enhancement to strengthen the preservation of textures and details [6,12,15]. However, edge-enhancement methods are heavily dependent on edge detection algorithms, which makes them insufficient to produce desired results, especially for weak edges. Later, it [5,19] is demonstrated that basic and generalized edge-enhancement methods will lose many noticeable textures, and preserving edges can hardly be equivalent to preserving visually sensitive textures. Structure-aware error diffusion (SAED) method [5] firstly achieves the essential features of structure-aware halftoning (SAH) method [19]. SAED has a higher efficiency than SAH, but yields lower structure similarity. Specially, it is not satisfactory for preserving structural details in the low-contrast region [13]. Recently, an adaptive contrast-aware mask is proposed to guide error diffusion for each pixel by contrast-aware halftoning (CAH) approach [14], which yields higher structure similarity without sacrificing speed. However, multiple tonal artifacts still exist (Figs. 1, 6, and 9).

Each of these above methods is still a partial solution of maintaining accurate tone consistency and exquisite structure preservation in a simple and effective way. Motivated by this challenging problem, we propose a novel structure-aware error-diffusion framework which is naturally compatible with the best tone-aware error diffusions [18,26]. Compared with the well-known structure-aware methods [5,14,19], our method can lead to better structure preservation due to the structure-sensitive threshold-modulation method. And this is irrelevant to special error-diffusion coefficients and processing path. Ostromoukhov's method [18] employs an off-line minimization process to search a set of diffusion coefficients for the near-optimal blue-noise spectra over different intensity levels. Here, the same Fourier spectra is produced by the further integration with the variable diffusion coefficients presented in Ostromoukhov's method. We further substitute Zhou and Fang's method [26] for Ostromoukhov's method to greatly improve the mid-tone quality in this paper (see Figs. 1, 6, and 9).

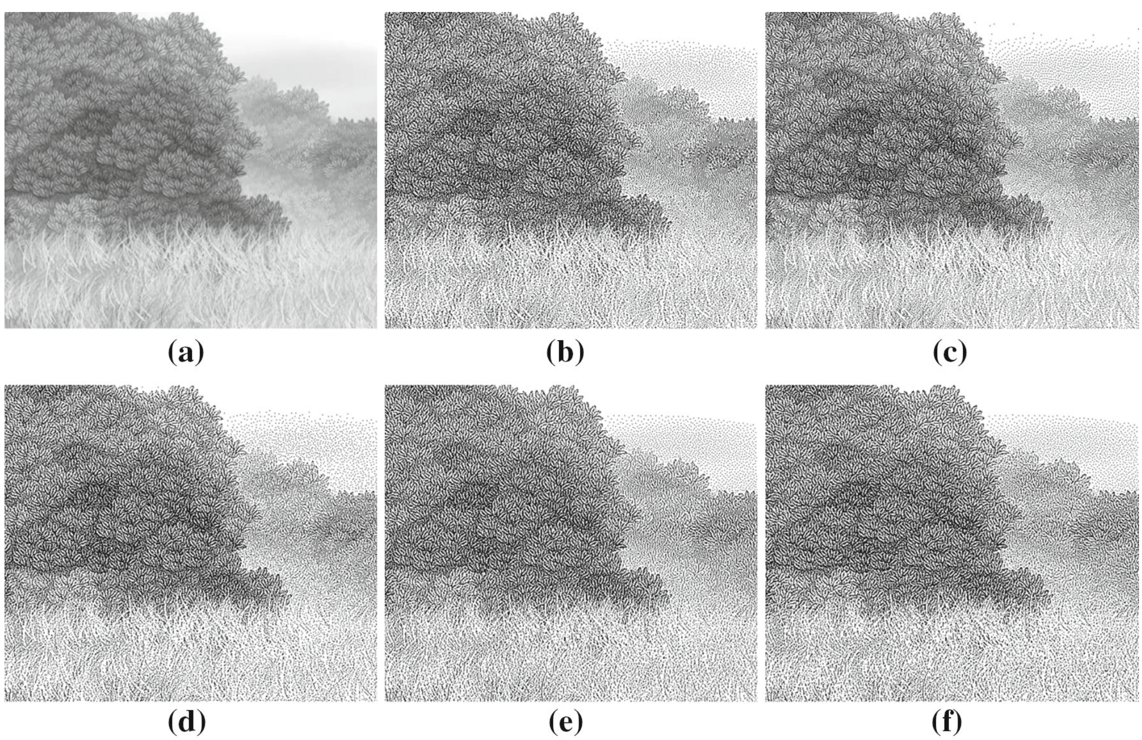


Fig. 1 Result comparison for the Tree image: **a** the input; **b** SAH; **c** the basic CAH, MSSIM = 15.51, PSNR = 21.13; **d** the variant CAH, MSSIM = 19.16, PSNR = 20.91; **e** our method using Ostromoukhov's technique, MSSIM = 19.78, PSNR = 21.51; **f** our method using Zhou and Fang's technique, MSSIM = 19.85, PSNR = 21.48. To view them with Acrobat reader using 250% zoom, please set the resolution to be 100 pixels/inch

The contributions of our paper are as follows:

– an adaptive entropy-constrained threshold-modulation scheme that preserves structural content without depending on special diffusion coefficients and processing path;
– a set of structure-aware error-diffusion schemes that integrate with the corresponding tone-aware methods and meanwhile obtain tonal and structural fidelity of high quality in a simple and efficient way.

The rest of this paper is organized as follows. Section 2 summarizes previous work. In Sect. 3, we present our algorithm. The result and analysis are given in Sect. 4. Finally, Sect. 5 concludes this paper.

2 Related work

Digital halftoning is a well-known color quantization technique. It always refers to the process of converting a continuous-tone image into a binary image. Digital halftoning techniques aim at producing a halftone image perceptually similar to continuous-tone image. Generally, digital halftoning algorithms are classified into the following three groups: dithering methods [4,16,22], neighborhood processes [5–7,14,18,26] and iterative algorithms [1,17,19]. The dithering methods are the fastest halftoning techniques but with deficient quality. Although the iterative algorithms are of the best quality, they are too computationally expensive for most real-world applications. The methods employing neighborhood processes can make the best tradeoffs between quality and performance, such as error diffusion. Error-diffusion algorithm has been an active field for years. Our methods follow the error-diffusion idea. Here, we mainly introduce the previous error-diffusion works directly related to our contributions.

Floyd and Steinberg firstly proposed error-diffusion algorithm [7] with the introduction of the error concept in digital halftoning. The principle idea is to distribute the quantization error of each pixel into its neighbors, for the purpose of maintaining intensity consistence on the larger scopes of original image and halftone result. This algorithm can produce relatively good result in a simple and easy manner, but it suffers from both visually harmful patterns and structural non-preservation. Our method produces good structure and tone similarities while maintaining the simplicity and efficiency of Floyd–Steinberg error diffusion.

It is commonly acceptable that good halftoning techniques always possess blue noise property. And the blue-noise property once bred a number of solutions to the harmful artifacts. Ostromoukhov [18] searched the optimum coefficients of each gray level to make its frequency spectrum approach the blue-noise frequency spectrum if at all possible. This method indeed improves halftone quality, especially in the light tone area. To overcome the mid-tone faults of Ostromoukhov's [18] method, Zhou and Fang [26] brought in a random function to adjust the original threshold. According to Zhou and Fang's experimental works, their method surmounts various shortcomings existing in the Floyd–Steinberg error diffusion more effectively. The absence of these annoying artifacts in this paper are based on [18] and [26]. Ostromoukhov's method is used as a standard base in [5,19]. We also refer to it for different quality comparisons in Sect. 4.

Although these aforementioned halftoning methods eliminate many tonal artifacts, the blurring and neglect of local textures and details are still their common problems. To impressively express structural features of original input image, numerous algorithms have been proposed, such as edge-enhancement error diffusion. To raise the edge information, Eschbach and Knox [6] used multiples of original image to modulate the threshold matrix. Following Eschbach and Knox's idea, several improved edge-enhancement techniques [8,12] are presented. The edge preservation of [8,12] is both based on the consideration of local luminance average. For a better edge quality than [8,12] devised a normalized spatial activity measure to generate information of edge enhancement. However, even these variations of edge-enhancement error diffusions cannot satisfy human visual perception of image textures. Many other shortcomings are highlighted in [5,14,19].

Structure-aware halftoning [19] (SAH) is an iterative optimization algorithm. This method builds an object function for measuring tone consistency and structure similarity between input image and halftone result. Then it tries to find the best solution through simulated annealing strategy. Chang et al. [5] first introduced structure preservation into the error diffusion, thus obtained a faster structure-aware method but with lower structure similarity. Lee et al. [13] employed a modified Laplacian operator to the quantizer thresholds, maintaining better low-contrast details than [5]. Recently, Li and Mould [14] employed contrast-aware diffusion coefficients to preserve the structures of original image, which led to higher structural similarity than the others. However, their structure-sensitive methods cannot avoid various annoying artifacts. This paper regards CAH [14] as an important reference for the structure-similarity measurement.

According to our theoretical deduction and analysis, the image-dependent threshold modulation should have potential to preserve visually identifiable structures. Despite its multiple different versions presented by many edge-enhancement error diffusions, they are far from not only adequate emphasis of details and textures but also the goal of removing tonal artifacts. To preserve human vision-sensitive textures via threshold modulation, the threshold function should contain the structural information of the original image. Similar to a digital unsharp masking, a low-pass filtering is applied to a copy of the original image, and the difference between the filtered image and the original image is utilized to determine information about spatially important structural details. The straightforward introduction of the texture information does not address the structure-aware issues, as the edge-enhancement approaches we mentioned before. The more satisfactory solution in this paper is benefiting from the adaptive entropy-constrained threshold modulation. The concept of entropy was initially a thermodynamic construct, it has been previously adopted in many other fields of study, including information theory, data compression, ecological economics, and image processing. But to our knowledge it has not been used in the threshold modulation of error diffusion. Compared with the state-of-the-art structure-aware methods, our approach makes a consistent promotion.

3 Our approach

The original error-diffusion method traverses the entire pixel set of an input image according to a scanline path. For each pixel, its current intensity is compared to a constant threshold (0.5), and the comparison determines its quantized result (1 or 0). According to error-diffusion coefficients (7/16, 3/16, 5/16 and 1/16), the quantization error is prorated among its 8-connected unprocessed neighboring pixels.

This paper employs an non-uniform thresholding from the entropy-constrained high-frequency components of the original image, to adaptively preserve the structural details. Meanwhile, the original distribution coefficients are modified to enhance the tone quality of our methods. Figure 2 illustrates the architecture comparison between the conventional error-diffusion method [7] and our approach. The detailed description of entropy-constrained threshold modulation is presented in Sect. 3.1. Section 3.2 provides tone-aware improvement.

3.1 Structural preservation

Many revised error-diffusion algorithms have been proposed to improve halftone quality by introducing spatial modulations to the threshold value. According to the above findings, the threshold modulation is recognized to be a powerful tool for error diffusion. In the threshold-modulated error diffusion, a threshold modulation function $t(\mathbf{x})$ is subtracted from the constant threshold t. Knox and Eschbach [11] has shown that the threshold-modified error diffusion with an image $f(\mathbf{x})$ generates a binary image, which is the same as the image produced by the classic error diffusion, but with an equivalent input image $f_{\mathrm{e}}(\mathbf{x})$ as the input. There exists a particular equivalent image, the spectrum of which can be

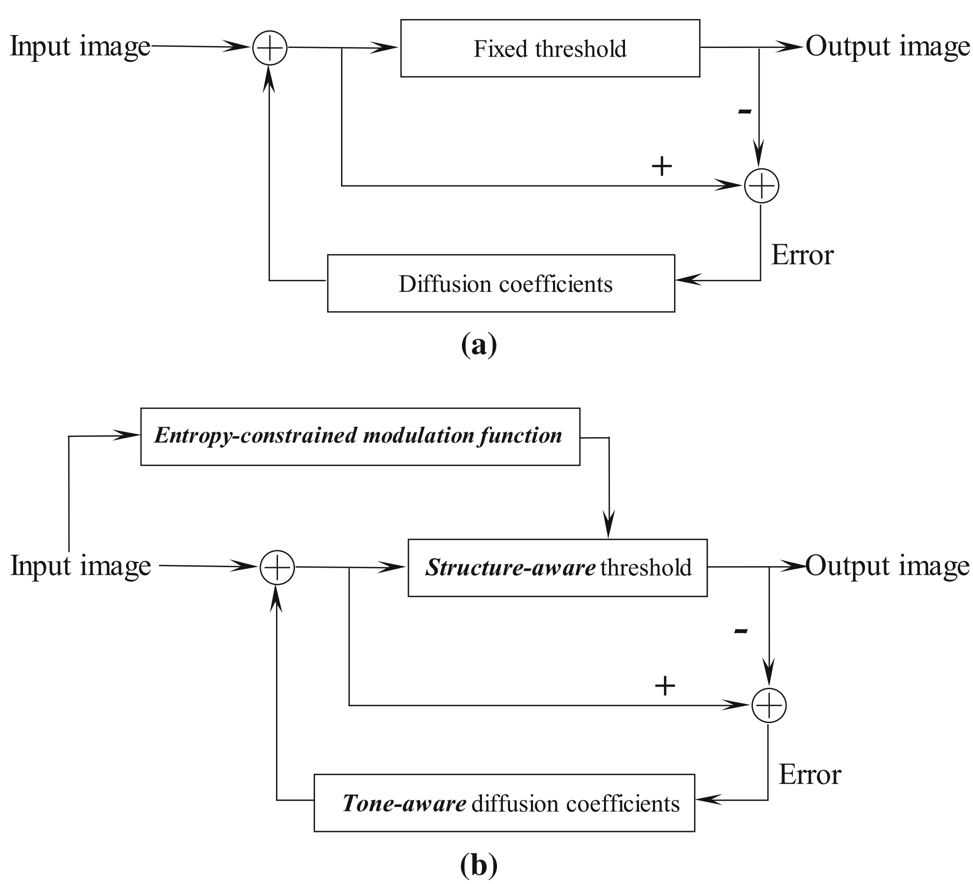


Fig. 2 Flowchart comparison: **a** the original error-diffusion method [7]; **b** our structure-aware methods

given by the following equation.

$$F_e(\omega) = F(\omega) + \Theta(\omega)T(\omega) \tag{1}$$

where the Fourier transform of a function is expressed by its corresponding capital letter. This relationship can be employed to predict the role that an input-dependent threshold modulation will play on the output error-diffusion image. According to the previous experimental verifications, the filter $\Theta(\omega)$ can let the high-frequency components of $T(\omega)$ pass into the equivalent input spectrum $F_e(\omega)$. The filter $\Theta(\omega)$ depends only on the error-diffusion coefficients within the approach. To better retain the structural features of the original image $f(\mathbf{x})$, its high-frequency contents can be extracted to modulate the threshold.

The structural information of an image is defined as the attributes that represent the structure of objects in the scene, independent of the average luminance and contrast [24]. It can be regarded as the strong interdependences of the image pixels primarily when they are close in the spatial domain. The appearances of the structural information (including edges, corners, etc.) can be significantly improved by promoting the high-frequency components of the image. Many error-diffusion approaches have more or less involved the structural characteristic extraction. The previous edge-enhancement techniques [8,12] emphasize the edge information of the original image and produce the halftone image with higher acutance, but those methods does not reproduce faithfully all subtle details. [5] presents a hypothesis that anisotropic filters should perform better than their isotropic counterpart in presence of anisotropic image structure. Based on this hypothesis, it employs the anisotropic Gabor filter. However, this algorithm cannot generate the satisfactory reproduction of the structural details in the low-contrast areas [13]. To address this problem of [5,13] uses the isotropic Laplacian filter to get structural information, not just the edges.

Our approach to structure-aware error diffusion is to *adaptively* modulate the threshold according to the high-frequency components of original image. Benefiting from this idea, we firstly generate the high-frequency contents only by the difference between a low-pass filtered copy and the original image, instead of more time-consuming anisotropic filter. The high-pass filtered result $g(\mathbf{x})$ with respect to the pixel $\mathbf{x}$ is obtained by

$$g(\mathbf{x}) = f(\mathbf{x}) - k^{-1} \sum_{\lambda \in \Lambda} f(\lambda) d(\lambda, \mathbf{x}) d\lambda \tag{2}$$

and

$$k = \sum_{\lambda \in \Lambda} d(\lambda, \mathbf{x}) d\lambda \tag{3}$$

where the low-pass filter coefficient $d(\lambda, \mathbf{x})$ measures the spatial closeness between the pixel $\mathbf{x}$ and its neighboring pixel λ. Λ is the set of the related nearby pixels. This paper only considers the shift-invariant low-pass filter. Then the high-frequency content $g(\mathbf{x})$ can be represented as

$$g(\mathbf{x}) = k^{-1} \sum_{\lambda \in \Lambda} (f(\mathbf{x}) - f(\lambda)) d(\lambda, \mathbf{x}) d\lambda \tag{4}$$

The function $g(\mathbf{x})$ involves the weighted differences between a center pixel and its neighbors. We specify $g(\mathbf{x})$ as the elementary threshold modulation function. It can be interpreted as the following: the threshold-modification strength of a center pixel relies on all neighbor pixels' impacts. The contribution of each neighborhood varies with their intensity difference, conversely with their spatial distance. As a result, a pixel that is darker than its neighborhoods, becomes more likely to be black. And a pixel that is lighter than its neighborhoods, becomes more likely to be white.

The entropy-constrained threshold modulation is driven by interesting experimental phenomenons of error diffusion [7]: the pixels with very low or high intensities always exert more active influence than the pixels with medium intensity in maintaining the local structure similarity. Applying this characteristic into the threshold-modification strength, the visually sensitive texture details can be more adaptively preserved.

To verify and analyse the effect of pixel intensity on structural preservation, the following experiment is set up for two representative image sequences (Fig. 3a, b). Since the pixel intensity is not the only influential factor on structural preservation, all the images of each image sequence are elaborately designed to avoid the influences of other possible factors. Here, an image sequence is composed of different input images but with very simple structures and the same high-frequency content $g(\mathbf{x})$. The difference between any consecutive images $f_n(\mathbf{x})$ and $f_{n-1}(\mathbf{x})$ is a constant grayscale image $d(\mathbf{x})$. A sequence of the average intensity of every input image forms an arithmetic progression.

For each image sequence, we determine the structure similarities between the input images and their respective halftone results by employing the mean structural similarity measure [24] with an identical configuration. The corresponding MSSIM-versus-Intensity graphs are depicted in Fig. 3c, e. These phenomena are not limited to the image series shown in this paper.

According to the experimental results, we plot approximate graphs of the effect of pixel intensity on structural preservation (see Fig. 3c, e). For an image sequence, the high-frequency contents of all images are all the same, but the preservation of structural information varies with the different intensities. Note that the structure preservation is diminished as the intensity approaches the center. In other words, the structural loss becomes more severe when the intensity gets closer to the threshold.

Driven by this phenomenon of the classic error diffusion, the concept of entropy is introduced to illustrate the fact. In

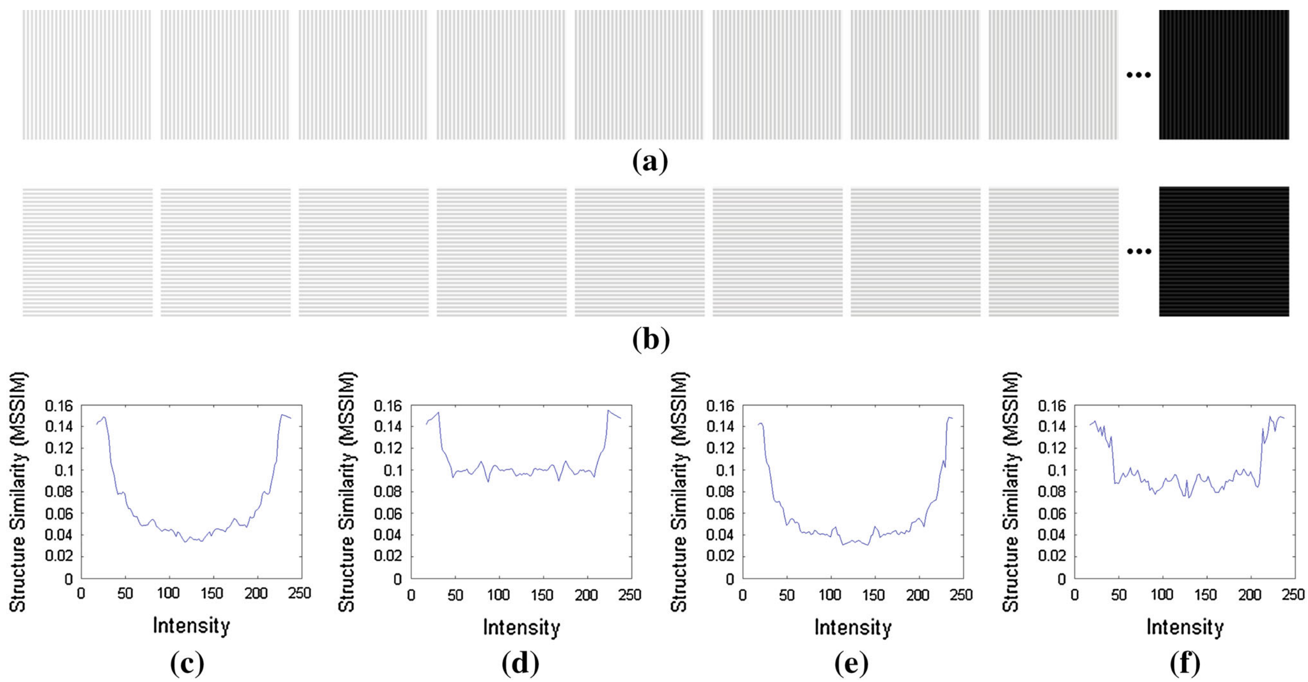


Fig. 3 The effect of pixel intensity on structural preservation: **a** an image sequence; **b** another image sequence; **c** the MSSIM-versus-Intensity graph of **a**; **d** the MSSIM-versus-Intensity graph of **a** after applying the entropy-constrained modulation. **e** The MSSIM-versus-Intensity graph of **b**; **f** the MSSIM-versus-Intensity graph of **b** after applying the entropy-constrained modulation

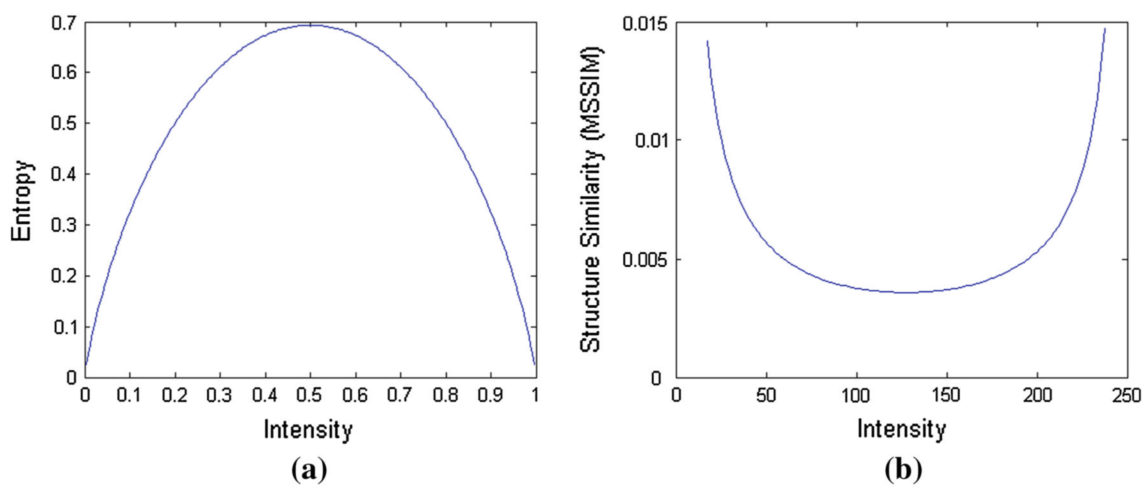


Fig. 4 **a** The entropy function used for threshold modulation; **b** The MSSIM-versus-Intensity graph of halftoning the constant-image sequence with the corresponding Intensity values

information theory, entropy is the measure of the amount of information that is missing before reception and is sometimes referred to as Shannon entropy [3]. The digital image entropy ε is concisely defined, and its basic formula is [9,10,20]

$$\varepsilon = -\sum_{k} p_k log_b p_k \tag{5}$$

where p_k is the probability associated with the gray level k, or the observed frequency of k. In the previous image sequence, the entropy values of all images are equal. But their respective halftoned results show different entropies. Let the symbol i denote the average intensity of an image. Then the percentage of white pixels is i in its resultant halftone image, and $1 - i$ represents the frequency of black pixels. The image entropy of this halftone result is calculated with

$$\varepsilon(i) = -i log_b i - (1 - i) log_b (1 - i) \tag{6}$$

Note, the entropy $\epsilon(i)$ (the information loss) achieves its maximum at $i = 0.5$, and this impact varies for different intensities i (as shown in Fig. 4a). It is acceptable that the halftone method always brings about the reduction of image content. To further explore the relevance between the intensity and structural similarity, we halftone the constant-image sequence with the corresponding intensity values used in Fig. 3c, e. The resultant graph is plotted in Fig. 4b. It can be noticed that the image entropy behaved very similarly to the inverted MSSIM. The higher entropy value corresponds to the distortion of more details. Since the intensity-dependent entropy is closely correlated to the structure preservation in error diffusion, it is adequate to connect them together. This paper regards Eq. 6 as the approximate estimation of the information loss caused by pixel intensity. The initial threshold-modification strength of a pixel is required to adaptively adjusted according to the distribution of its surrounding pixels' intensities. Concretely, the contribution of each neighboring pixel is directly multiplied by the distortion estimation which corresponds to its intensity. In other words, the greater loss from the pixel value, the greater emphasis on the high-frequency component. Based on this assumption, this paper proposes an entropy-constrained threshold modulation to adaptively enhance the structural details of original image.

$$t(\mathbf{x}) = c \sum_{\lambda \in \Lambda} \varepsilon(f(\mathbf{x}))(f(\mathbf{x}) - f(\lambda))d(\lambda, \mathbf{x})\mathrm{d}\lambda \tag{7}$$

In our experiments, the shift-invariant Gaussian filtering is utilized. Adjusting the coefficient c can directly increase or decrease the structure similarity. To verify this proposed assumption, the two representative image sequences are, respectively, halftoned by Floyd–Steinberg error diffusion with our entropy-constrained threshold modulation. The new results are shown in Fig. 3d, f. It can be seen the unsatisfactory effect of pixel intensity on preserving image structure is hugely diminished. Figure 5 shows that the results of our threshold modulation function acted on Floyd–Steinberg error diffusion. It verifies that the above threshold modulation accomplishes the structure preservation in the error diffusion successfully. However, many related tonal artifacts inherited from the original error diffusion still exist (Fig. 6). Next, this paper will discuss the removal of such artifacts.

3.2 Tonal improvement

Although the usage of the entropy-constrained threshold modulation function can effectively improve the structure preservation in the original error diffusion, many tonal artifacts still exist in smooth regions. Because the intensity gradients in smooth regions mostly stay small, the corresponding adjustments on the fixed threshold are very weak, even insignificant. Therefore, these artifacts are mainly due to the defects of Floyd–Steinberg error diffusion.

To address these problems, we introduce two techniques to improve the tone quality of our methods separately. One is the variable-coefficient error diffusion proposed by Ostromoukhov [18], the other is Zhou and Fang's modified method [26] based on Ostromoukhov's work. One common place of the two methods is generating different suitable error-diffusion coefficients for different intensity levels via an off-line optimization. They both discard the raster scanning order, supplanted by the serpentine traversal path. Their main difference is that the approach proposed by Zhou and Fang adds a random perturbation to modulate the threshold for breaking up the artifacts existing in the mid-tone areas. And the modulation strengths are different for different gray levels in Zhou and Fang's method.

The advantages of the methods can be observed from Figs. 6 and 9. Many artifacts are removed in the light tone

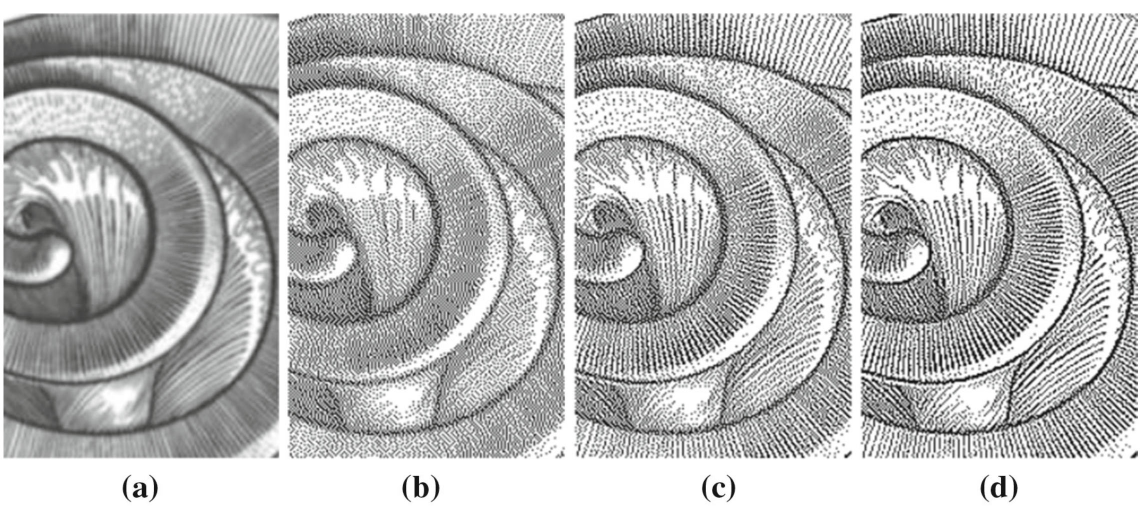


Fig. 5 Applying our threshold modulation on Floyd–Steinberg error diffusion: **a** the input; **b** Floyd–Steinberg error diffusion; **c** our threshold modulation with $c = 7.6$ on Floyd–Steinberg error diffusion; **d** our threshold modulation with $c = 16.4$ on Floyd–Steinberg error diffusion. To view them with Acrobat reader using 250 % zoom and 100 pixels/inch resolution

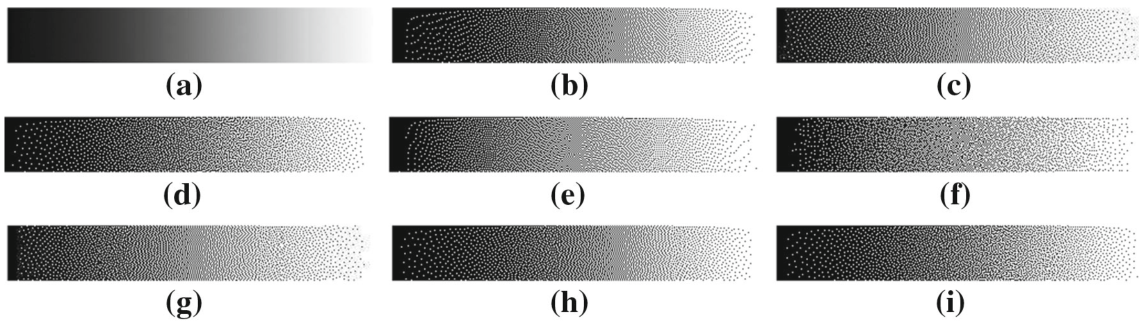


Fig. 6 Result comparison for the Ramp image: **a** the input; **b** our threshold modulation with $c = 1$ on Floyd–Steinberg error diffusion; **c** Ostromoukhov's technique; **d** Zhou and Fang's technique; **e** the basic CAH; **f** the variant CAH; **g** SAH; **h** our method using Ostromoukhov's technique when $c = 1$; (i) our method using Zhou and Fang's technique when $c = 1$. To view them with Acrobat reader using 200 % zoom and 100 pixels/inch resolution

and dark tone areas. The visual anomalies appearing at some levels around mid-tones are also eliminated by using Zhou and Fang's method. Consequently, the mid-tone quality of this method is markedly improved.

4 Results

This section mainly compares ours and state-of-the-art halftoning methods concerning the quality and performance. The comparison of the halftone quality always includes the subjective observation and the objective measurement. The objective measurement mainly employs the common techniques adopted by the recent structure-aware methods. The quality comparison should focus on the following aspects: tone reproduction, structure preservation and blue-noise property. Note that our approach directly inherits the desirable blue-noise property from the tone-aware techniques [18,26] (see Fig. 7). After the quality comparison, the performances of the previous structure-aware methods are compared with ours. The motivation of this paper is to preserve textural details in halftone image, but pursuing a structure-aware method without good tone reproduction is not our goal. The test images used in our experiments mostly come from the common images used by these structure-aware techniques. These images include many smooth regions, like sky and blurred background, and various textural details, such as fur, feathers, and tissues (Fig. 1, 8 and 9).

4.1 Quality evaluation

4.1.1 Visual comparison

Figure 1 shows that the halftone appearance of the feather details in fog are superior to CAH [14] and SAH [19]. Besides this, many tonal artifacts appear in the smooth region of the CAH results. Our methods perform better than its basic and variant methods, such as the sky regions in the images. Another similar case can be observed from the sky areas in Fig. 9.

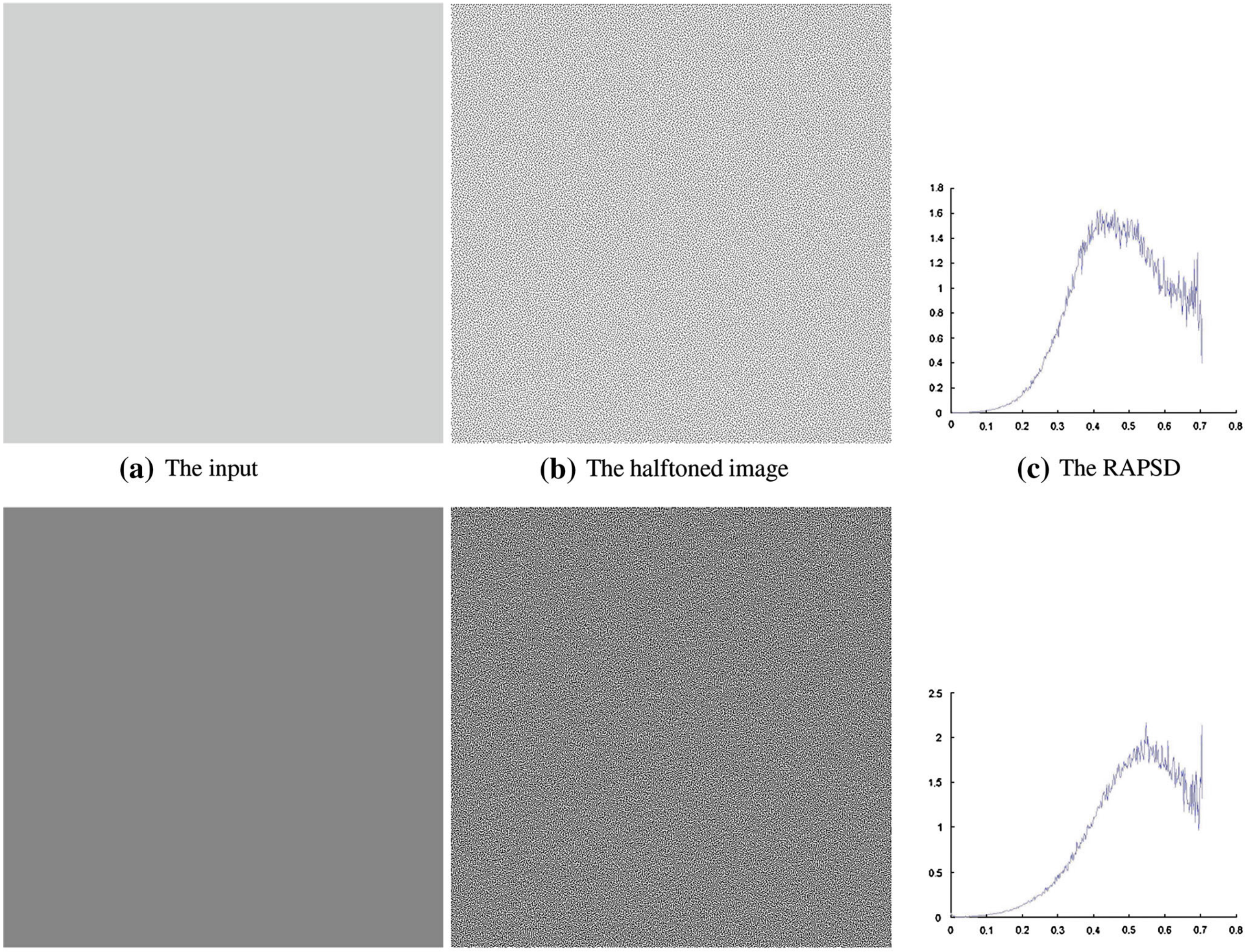
In the mid-tone quality, the problems of "visually harmful alignment" and "transient effects" [26] still exist, especially in Figs. 1 and 9. The integration of Zhou's method and our structure-aware technique breaks up these artifacts, and obviously improves our entire tone reproduction. To further verify this advantage, this paper continues to conduct an experiment on the grayscale ramp. The results are illustrated in Fig. 6.

Thus, our methods not only contain commendable structure preservation, but also inherit the splendid tone reproduction from Ostromoukhov's and Zhou's methods. In this way, both structure preservation and tone reproduction are given enough consideration.

4.1.2 Objective measures

Here, we employ public objective measurements to evaluate our methods quantitatively. Firstly, the tests on tone consistence and structural similarity are carried out separately. Then we compare our test results with other methods'. Finally, our methods generate better results on both sides than the recent structure-aware methods.

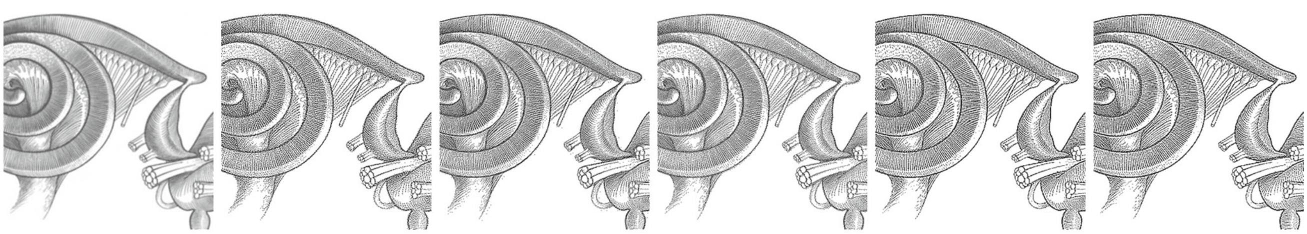
Tone consistence is measured by PSNR (peak signal-to-noise ratio). PSNR is originally used to estimate the restored image quality from the lossy image compression. Then SAH, SAED and CAH all utilize it to measure the tone consistence in halftone fields. And their experimental results indicate that Ostromoukhov's method is better than theirs on the tone consistence. In fact, Ostromoukhov's and Zhou's methods both possess excellent tone reproduction. Unlike SAED and CAH, our approach preserves the structure information only by threshold modulation, which makes our methods compatible with Ostromoukhov's and Zhou's methods. The balance between tone consistence and structure preservation can be adjusted only by changing the proportional coefficient C.



(a) The input **(b)** The halftoned image **(c)** The RAPSD

(d) The input **(e)** The halftoned image **(f)** The RAPSD

Fig. 7 Blue-noise analysis. *Top row* results for a constant-grayness image (grayness = 0.820) by our method using Ostromoukhov's technique. *Bottom row* results for a constant-grayness image (grayness = 0.525) by our method using Zhou and Fang's technique. From *left* to *right* the input; the halftoned image; the radially averaged power spectrum density (RAPSD). To view them with Acrobat reader using 500 % zoom and 100 pixels/inch resolution



(a) **(b)** **(c)** **(d)** **(e)** **(f)**

Fig. 8 Result comparison for the Snail image: **a** the input; **b** SAH, MSSIM = 44.75, PSNR = 19.72; **c** SAED; **d** the basic CAH, MSSIM = 43.86, PSNR = 19.39; **e** our method using Ostromoukhov's technique, MSSIM = 47.09, PSNR = 19.94; **f** our method using Zhou and Fang's technique, MSSIM = 47.09, PSNR = 19.95. To view them with Acrobat reader using 400 % zoom and 100 pixels/inch resolution

When C is equal to 0, our algorithms always gain the best PSNR scores, and now the algorithms are separately the same as Ostromoukhov's and Zhou's methods in fact.

MSSIM (mean structural similarity measure) is proposed to assess the structure similarity. Later SAH applies MSSIM on the Gaussian-filtered input and output image, so do CAH

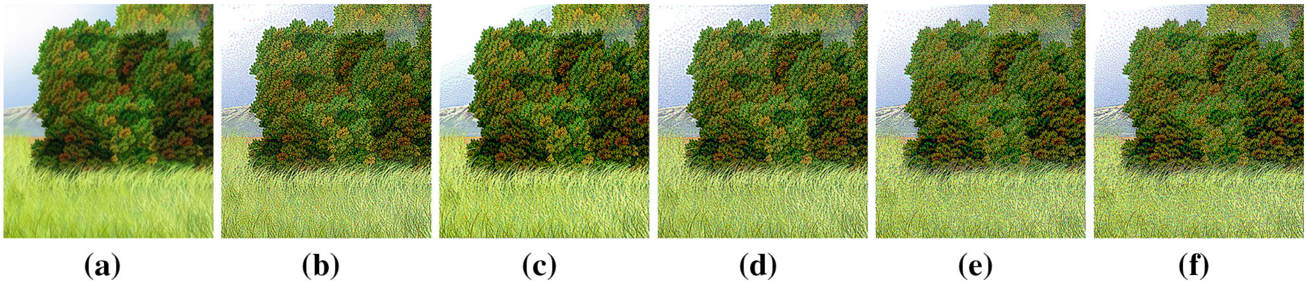


Fig. 9 Result comparison for the color image: **a** the input; **b** SAH; **c** the basic CAH; **d** the variant CAH; **e** our method using Ostromoukhov's technique; **f** our method using Zhou and Fang's technique. To view them with Acrobat reader using 400 % zoom and 100 pixels/inch resolution

Table 1 The MSSIM measurement for various images

Image	Mole	Portrait	Ribbon	Arm	Bat	Cat	Knee	Snail
Ours with Zhou	12.40	31.08	35.90	56.74	26.43	15.31	47.15	47.09
Ours with Ostromoukhov	12.68	31.53	35.85	57.36	25.78	15.24	46.26	47.09
The basic CAH	10.63	28.77	32.92	55.11	25.56	11.42	45.63	43.86
SAH	10.11	27.45	28.51	54.79	26.78	12.30	45.34	44.75
SAED	–	–	32.37	55.10	–	–	43.59	–
Ostromoukhov	6.16	18.61	28.36	38.45	16.17	6.73	29.51	38.03

Table 2 The PSNR measurement for the results used in Table 1

Image	Mole	Portrait	Ribbon	Arm	Bat	Cat	Knee	Snail
Ours with Zhou	34.37	33.23	27.24	22.51	31.80	32.42	33.51	19.95
Ours with Ostromoukhov	34.68	33.30	27.40	22.44	32.83	33.55	35.28	19.94
The basic CAH	31.88	33.14	26.88	22.42	32.71	32.39	33.31	19.39
Ostromoukhov	41.27	39.67	27.88	22.60	34.60	40.88	39.82	19.92

and SAED. The statistical results in Table 1 show that our methods produce better structural similarity than the other algorithms. The results of objective measures corroborate the same conclusion brought by the above visual comparison.

In order to be more objective about the comparison, we try to find such a halftone result that simultaneously obtains better scores on both tone consistency and structure similarity. The basic and variant CAH methods achieve better structure preservation than SAH and SAED. Compared to its basic method, its variant method introduces the priority heap to provide better structure detail. But this priority-based scheme greatly decreases the tone consistency. Hence, we choose the basic CAH method as a reference. Despite the fact that SAH is not an error-diffusion method, we still carry out the similar comparison with SAH.

The PSNR and MSSIM test results are listed in Tables 1 and 2. It is found that our methods outperform CAH in tone matching while ensuring better structure similarity. Likewise, the comparison between SAH and ours gives the same judgement (see Table 3). In conclusion, our methods are the error diffusions with outstanding comprehensive quality, from tone reproduction to structure preservation.

4.2 Performance review

For both SAED and CAH, the degree of structure detail preservation mainly depends on the size of the neighborhood window. Increasing the size always enhances the structure preservation, but costs more computation time. Unlike them, the degree of structure detail preservation mainly rests with the scaling factor of our threshold modulation function. Namely, the enlargement of the factor can bring a higher structure similarity, without increasing computation time.

Because the quality and performance of these structure-aware methods are related to the choice of the neighborhood window size, it is necessary to discuss the most suitable sizes of these methods for the best tradeoff between quality and speed. The 16×16 kernel can make SAED reach the best balance between quality and performance, and the 7×7 mask is adopted by CAH. According to the experimental results, a smaller region (3×3) is enough for our methods. Our methods only need to consider the neighbors within the 3×3 region.

For a 512×512 image, the basic CAH expends 0.492 s on an Intel Core Duo CPU E8400@ 3.0 GHz with 3 GB RAM,

Table 3 The joint measurement for various images using MSSIM and PSNR

Image	Mole	Portrait	Ribbon	Arm	Bat	Cat	Knee	Snail	Tree
MSSIM of ours with Zhou	10.89	29.41	35.35	55.38	26.79	13.59	46.39	46.55	17.35
MSSIM of ours with Ostromoukhov	10.96	30.51	35.09	55.68	28.20	13.51	45.60	46.24	17.50
MSSIM of SAH	10.11	27.45	28.51	54.79	26.78	12.30	45.34	44.75	15.39
PSNR of ours with Zhou	36.89	35.21	27.41	22.59	31.45	35.12	34.35	19.95	21.60
PSNR of ours with Ostromoukhov	38.00	35.29	27.59	22.57	31.46	36.40	36.00	19.95	21.58
PSNR of SAH	35.71	35.04	25.70	22.33	31.42	30.22	35.94	19.72	21.56

Table 4 Performance of our approach [Intel(R) Core(TM)2 Duo CPU T7250 @ 2.00 GHz (2 CPUs) and 2,046 MB RAM]

Method	Time (CPU, s)
Ours with Zhou	0.0352
Ours with Ostromoukhov	0.0343

while the variant CAH takes 2.955 s. And the computation time for our methods is shown in Table 4.

In summary, our approach takes less time, and achieves better halftone quality. The tone consistence and structure similarity are both superior to the previous structure-aware methods.

5 Conclusion

In the field of error diffusion, threshold modulation and modifying error-diffusion coefficients are two important techniques to improve halftone quality. This paper constructs a entropy-constrained threshold modulation function, which can fairly accomplish the structure preservation in error diffusion. At the same time, there still exist many tonal artifacts of original error diffusion. This paper further introduces recent variable-coefficient techniques with excellent tone reproduction, so that the whole tone quality of our methods are improved evidently. Finally, our paper gives the detailed experimental results from the various comparisons with recent state-of-the-art structure-aware methods. Whether visual comparison or objective quality evaluation, the results all indicate that our methods have obvious superiority on both tone consistency and structure similarity. Especially, our methods also run faster than them.

In addition, the combination of our structure-aware threshold modulation and Zhou's method does not have flawless exhibition, because Zhou and Fang's method also employs threshold modulation. Although their random turbulence to the fixed threshold greatly improves our mid-tone quality, there still exists a little adverse influence to the preservation of tiny details. We hope to find a more suitable method to improve the mid-tone quality for our methods in the future work.

Finally, to cope with a color image, our approach handles each color channel separately, and combine their results into the halftone of the color image. This simple scheme may ignore some useful features of color image, and thus further investigation is needed in the future.

References

1. Analoui, M., Allebach, J.P.: Model-based halftoning using direct binary search. In: Proceedings of SPIE, vol. 1666, pp. 96–108 (1992)
2. Asano, T.: Digital halftoning algorithm based on random space-filling curve. In: IEEE International Conference on Image Processing, vol. 1, pp. 545–548 (1996)
3. Balian, R.: Entropy, a protean concept. In: Poincaré Seminar 2003, Progress in Mathematical Physics, p. 119 (2004)
4. Bayer, B.E.: An optimum method for two-level rendition of continuous-tone pictures. In: IEEE International Conference on Communications, pp. 26:11–26:15. IEEE, New York (1973)
5. Chang, J., Alain, B., Ostromoukhov, V.: Structure-aware error diffusion. ACM Trans. Graph. (TOG) 2**8**(5), 162:1–162:8 (2009)
6. Eschbach, R., Knox, K.T.: Error-diffusion algorithm with edge enhancement. J. Opt. Soc. Am. A **8**(12), 1844–1850 (1991)
7. Floyd, R.W., Steinberg, L.: An adaptive algorithm for spatial greyscale. Proc. Soc. Inf. Disp. **17**(2), 75–77 (1976)
8. Hwang, B.W., Kang, T.H., Lee, T.S.: Improved edge enhanced error diffusion based on first-order gradient shaping filter. In: IEA/AIE, vol. 3029, pp. 473–482 (2004)
9. Kapur, J.N., Sahoo, P.K., Wong, A.K.C.: A new method for gray-level picture thresholding using the entropy of the histogram. Comput. Vis. Graph. Image Process. **29**(3), 273–285 (1985)
10. Khellaf, A., Beghdadi, A., Dupoisot, H.: Entropic contrast enhancement. IEEE Trans. Med. Imaging **10**(4), 589–592 (1991)
11. Knox, K.T., Eschbach, R.: Threshold modulation in error diffusion. J. Electron. Imaging **2**(3), 185–192 (1993)
12. Kwak, N.J., Ryu, S.P., Ahn, J.H.: Edge-enhanced error diffusion halftoning using human visual properties. In: Proceedings of the 2006 International Conference on Hybrid Information Technology, Vol. 01, ICHIT '06, pp. 499–504 (2006)
13. Lee, H.S., Kong, K.K., Hong, K.S.: Laplacian based structure-aware error diffusion. In: Proceedings of the International Conference on Image Processing, pp. 525–528 (2010)
14. Li, H., Mould, D.: Contrast-aware halftoning. Comput. Graph. Forum **29**(2), 273–280 (2010)
15. Li, X.: Edge-directed error diffusion halftoning. IEEE Signal Process. Lett. **13**(11), 688–690 (2006)

16. Mitsa, T., Parker, K.J.: Digital halftoning technique using a blue-noise mask. J. Opt. Soc. Am. A **9**(11), 1920–1929 (1992)
17. Neuhoff, D.L., Pappas, T.N., Seshadri, N.: One-dimensional least-squares model-based halftoning. Proc. ICASSP **14**, 1997 (1997)
18. Ostromoukhov, V.: A simple and efficient error-diffusion algorithm. In: Proceedings of ACM SIGGRAPH, SIGGRAPH '01, pp. 567–572 (2001)
19. Pang, W.M., Qu, Y., Wong, T.T., Cohen-Or, D., Heng, P.A.: Structure-aware halftoning. ACM Trans. Graph. (TOG) **27**(3), 89:1–89:8 (2008)
20. Pun, T.: Entropic thresholding, a new approach. Comput. Graph. Image Process. **16**(3), 210–239 (1981)
21. Ulichney, R.: Digital Halftoning. MIT Press, Cambridge (1987)
22. Ulichney, R.A.: Dithering with blue noise. Proc. IEEE **76**, 56–79 (1988)
23. Velho, L., Gomes, J.d.M.: Digital halftoning with space filling curves. In: Proceedings of ACM SIGGRAPH, SIGGRAPH '91, pp. 81–90 (1991)
24. Wang, Z., Bovik, A.C., Sheikh, H.R., Simoncelli, E.P.: Image quality assessment: from error visibility to structural similarity. IEEE Trans. Image Process. **13**(4), 600–612 (2004)
25. Zhang, Y., Webber, R.E.: Space diffusion: an improved parallel halftoning technique using space-filling curves. In: Proceedings of ACM SIGGRAPH, SIGGRAPH '93, pp. 305–312 (1993)
26. Zhou, B., Fang, X.: Improving mid-tone quality of variable-coefficient error diffusion using threshold modulation. ACM Trans. Graph. (TOG) **22**(3), 437–444 (2003)

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