LAPLACIAN BASED STRUCTURE-AWARE ERROR DIFFUSION

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ABSTRACT

In this paper, we propose a new halftoning scheme that preserves the structure and tone similarities of images while maintaining the simplicity of Floyd-Steinberg error diffusion. Our algorithm is based on the Floyd-Steinberg error diffusion algorithm, but the threshold modulation part is modified to improve the over-blurring issue of the Floyd-Steinberg error diffusion algorithm. By adding some structural information on images obtained using the Laplacian operator to the quantizer thresholds, the structural details in the textured region can be preserved. The visual artifacts of the original error diffusion that is usually visible in the uniform region is greatly reduced by adding noise to the thresholds. This is especially true for the low contrast region because most existing error diffusion algorithms cannot preserve structural details but our algorithm preserves them clearly using threshold modulation.

Our algorithm has been evaluated using various types of images including some with the low contrast region and assessed numerically using the MSSIM measure with other existing state-of-art halftoning algorithms. The results show that our method performs better than existing approaches both in the textured region and in the uniform region with the faster computation speed.

Index Terms— Halftoning, error diffusion, structure-aware, Laplacian, threshold modulation, low contrast

1. INTRODUCTION

Halftoning is an algorithm used to represent an original continuous gray-level image by a binary image. The goal of halftoning is to describe the original image as closely as possible using binary levels. Many halftoning algorithms have been proposed to attain this goal. The error diffusion approach by Floyd-Steinberg[1] is a good example of this type of algorithm as it is simple, fast, and produces good quality results. However, it does have the following drawbacks. First, this algorithm produces visual artifacts such as worm artifacts and annoying patterns, especially in uniform regions. Secondly, it results in over-blurred edges in textured regions.

To reduce the visual artifacts, Ostromoukhov[2] proposed a variable-coefficient error diffusion algorithm using 256 different error filter coefficient sets. Also, Li and Allebach[3] created a tone-dependent error diffusion algorithm, which changes filter weights and quantizer thresholds depending on the input gray levels. Zhou[4] demonstrated a variable threshold modulation method for removing visual artifacts in halftoning, especially at mid-tones. These algorithms are designed to deal with the uniform region without creating disruptive patterns. However, they don’t seem to be able to preserve the fine texture of the original image, as is shown in the dotted circled area of Figure 2(b).

To preserve the fine texture of images, Eschbach et al.[5] proposed an edge-enhanced error diffusion algorithm with a preprocessing filter which enhances images by multiplying them by a constant value. Hwang et al.[6] used the spatial information of an original image, and Kwak et al.[7] used human visual properties. Feng et al.[8] proposed an edge enhancement error diffusion algorithm using impact functions which vary depending on the magnitude of the gradient. However, these algorithms do not provide satisfactory results, particularly in the fine textured region. Pang et al.[9] proposed an optimization-based halftoning approach which preserves the structure and tone similarities between the original and the halftone images. This algorithm performed well both in the uniform region and in the textured region. However, it may have limited practical application potential because it adopts an iterative optimization method causing a high computational requirement. Chang et al.[10] proposed a structure-aware error diffusion method using a frequency- and orientation-dependent Gabor filter. It produces images with a quality comparable to those presented in Pang's[9] method, but gives a much faster result. However, this algorithm doesn't give satisfactory results in terms of preserving structural details in the low contrast region.

In this paper, we introduce a new approach which preserves the fine texture of the original image while maintaining tone similarity with a low computational cost compared to the original error diffusion algorithm. To satisfy the computational simplicity requirements and to reduce the visual artifacts in the uniform region, our algorithm is based on the Floyd-Steinberg error diffusion algorithm using threshold modulation[11]. This method was designed to remove only the visual artifacts, but our algorithm has varying quantizer thresholds which depend on the structural information obtained by Laplacian filtering. Using this scheme, our algorithm produces visually pleasing patterns in the uniform region, and also preserves fine details in the textured region even in low contrast regions. In our experiments, our algorithm exhibits the best results among all of the tested algorithms. Section 2 describes the overall flow and technical details of the proposed error diffusion algorithm. The experiments are outlined in section 3, we conclude our work in section 4.

2. THE PROPOSED ALGORITHM

2.1. The Overall Flow of The Proposed Algorithm

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The Floyd-Steinberg error diffusion algorithm for each pixel consists of three steps. First, a modified input of each pixel is formed using the sum of the input value plus the "diffused" past errors. In the second step, this modified input is quantized to yield the output using a constant threshold. Lastly, the quantization error is calculated as the difference between the modified input and output.

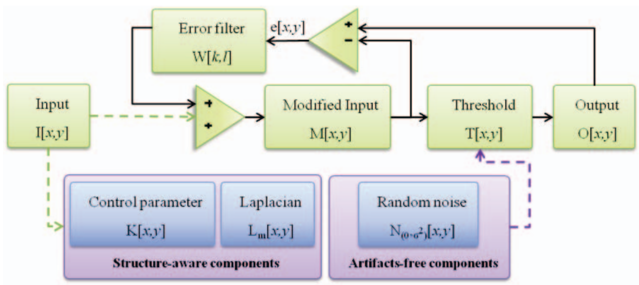

Figure 1. Block diagram of the proposed error diffusion algorithm.

The proposed error diffusion algorithm is somewhat similar to Floyd-Steinberg's. However, it has a major difference because the thresholds change depending on structural information and then random noise is added.

The threshold modulation part of the proposed algorithm consists of structure-aware components and artifacts-free components (as illustrated in Figure 1). The role of the structure-aware components is to extract structural information from an input image. This comes from the concept that we can get better halftone quality if the structural information influences the quantizer thresholds. This means that we can improve the halftone quality by controlling the quantizer thresholds in the textured region.

For the low contrast region, most existing error diffusion algorithms cannot preserve the fine details since they cannot operate effectively enough to extract the structural information from the low contrast region. In order to preserve the fine details in the low contrast region, our algorithm adopts the gain parameter, $K[x,y]$. It is a weighting function which is inversely proportional to the local standard deviation. The larger it is, the more we can preserve fine details in low contrast regions. The artifacts-free components reduce the visual artifacts. It is based on Knox's idea[11] that visual artifacts can be reduced by adding noise to thresholds.

Our algorithm constructs a threshold matrix based on the structural information and noise instead of the constant quantizer thresholds.

2.2. Formulation of the Proposed Algorithm

To preserve the fine texture in the textured region, we need to construct a threshold matrix whose elements vary depending on the structural information as mentioned above. The structure-aware threshold matrix $T_s[x,y]$ is obtained using the following equation:

$$T_s[x,y] = K[x,y] \cdot L_m[x,y], \tag{1}$$

where $K[x,y]$ is the gain parameter and $L_m[x,y]$ is the modified Laplacian-filtered image. We employ Laplacian filtering to get the structural information including the edges, corners, and lines. There are many ways to get structural information, but Laplacian filtering is the simplest and the most efficient. Directly employing the Laplacian filtered image to the threshold matrix gives rise to the over-enhancement of edges, so we use a modified Laplacian-filtered image by clipping the minimum $(-L_{max})$ and the maximum (L_{max}). In all of our experiments, we set $L_{max} = 128$.

For the low contrast region, we need to control the gain parameter to preserve the fine details. In order to get good results in low contrast images, the gain parameter, $K[x,y]$ uses local standard deviation and global standard deviation at the same time. With these two values, it can locally preserve fine details in all areas of an image. It is formulated according to the following equation:

$$K[x,y] = \frac{C}{\Sigma} \times \left(\frac{|\sigma[x,y] - \sigma_{max}|}{\sigma_{max} - \sigma_{min}} \right) + C, \tag{2}$$

where C is a scale factor, Σ is the global standard deviation of an input image and, $\sigma[x,y]$ is the local standard deviation. σ_{max} / σ_{min} is defined as the maximum / minimum values of $\sigma[x,y]$. In all of our experiments, we set C = 5. A window size of 11 x 11 pixels is used to compute the local standard deviation. In order to further preserve the fine texture, all that needs to be done is to just to increase the value of C.

To reduce the visual artifacts, we also need to construct a threshold matrix by adding Gaussian random noise. The artifacts-free threshold matrix $T_A[x,y]$ is obtained using the following equation:

$$T_A[x,y] = N_{(0,\sigma^2)}[x,y], \tag{3}$$

where $N_{(0,\sigma^2)}[x,y]$ is the Gaussian random noise with a zero mean. The standard deviation, σ is set to 10% of the maximum gray value.

The final threshold matrix $T[x,y]$ can be evaluated from the following equation:

$$T[x,y] = T_S[x,y] + T_A[x,y], \tag{4}$$

The other parts of block diagram (Figure 1) are similar to the Floyd-Steinberg error diffusion algorithm. The modified input, $M[x,y]$, and quantization error, $e[x,y]$, are obtained using the following equation :

$$M[x,y] = I[x,y] + \sum_{k,l} w[k,l]e[x-k, y-l], \tag{5}$$

$$e[x,y] = M[x,y] - O[x,y], \tag{6}$$

where $I[x,y]$ is the input image, $w[k,l]$ is the weight for error propagation in the $[k,l]$ direction, and $O[x,y]$ is the output binary image.

3. EXPERIMENTAL RESULTS

To evaluate the performance of our algorithm, tests on various types of images that include the textured region, uniform region and low contrast region were carried out. In addition to the subjective visual comparison, we carried out objective evaluations:

evaluating structural preservation and the processing time. We compared our algorithm with the three best performing halftoning algorithms. The first one is Ostromoukhov's algorithm which is a variable-coefficient error diffusion[2] method. It results in the best non-structure-aware performance among the halftoning algorithms. The second one is the state-of-the-art structure-aware halftoning algorithm proposed by Pang et al[9]. The last one is the structure-aware error diffusion halftoning algorithm proposed by Chang et al[10]. The last two algorithms result in the best performance among the structure-aware halftoning algorithms.

3.1. Objective Evaluation

To measure the structural preservation, we employed a structural similarity index measurement (SSIM)[12] to quantify the structural difference between the halftone result and the original grayscale image. An MSSIM (mean SSIM) that evaluates the overall image quality is obtained by taking the average of the SSIM for all pixels. The valid range of MSSIM is [0, 1], with higher values indicating a higher similarity. In our case, we apply the MSSIM value calculation method proposed by Pang[9] and use an 11×11 pixel local window size.

Table 1 show the MSSIM values for the set of test images shown in Pang's paper[9]. As can be seen in Table 1, for the highly structured region, the MSSIM values of our algorithm are around 10% higher than Pang's algorithm and 5% higher than Chang's algorithm. For the low contrast region, our algorithm results in MSSIM values as much as 25% higher than the other two algorithms which have been regarded as state-of-the-art halftoning algorithms.

Our algorithm was implemented on a PC with an Intel Core™2 2.13GHz CPU and 3GB of memory. The processing time for our method is almost the same as that of Ostromoukhov's algorithm. Our method runs three orders of magnitude faster than Pang's algorithm and about ten times faster than Chang's algorithm (Table 2), even though they used GPU to accelerate the processing time.

Table 1. MSSIM comparison on various images.

	Ostromoukhov's [2]	Pang's [9]	Chang's [10]	Ours
Arm	0.494	0.549	0.537	**0.557**
Ribbon	0.278	0.277	0.317	**0.339**
Bush	0.124	0.160	0.133	**0.186**
Cat	0.063	0.120	0.112	**0.146**
Road	0.194	0.292	0.247	**0.305**
Snail	0.390	0.434	0.411	**0.444**

Table 2. Comparison of the average processing time (sec).

Image Size	Ostromoukhov's [2]	Pang's[9] with GPU	Chang's[10] with GPU	Ours
256 × 256	0.009	27	0.11	**0.011**
512 × 512	0.037	120	0.22	**0.034**

3.2. Visual Comparison

Although the performance of structure-aware halftoning algorithms is a little bit lower and closer to ours in terms of MSSIM values, differences in image quality can be noticed in the regions with blurriness and weak edges. In the dotted circled area of Figure 2(b), Ostromoukhov's method lost almost all of the structural details and blurred that region. In that area in Figure 2(c), Pang's method shows its failure to track the weak edges. In Figure 2(d), Chang's method looks more similar to the original image than Pang's, but it's still not satisfactory. In contrast, our method faithfully preserves the weak edges.

Particularly in the low contrast region, as shown in the circled area of Figure 3, our method preserves the fine details in the textured region, and shows an even better performance than other methods. In the most regions with a fine texture, the original lines disappear in Ostromoukhov's, Pang's and Chang's results, but only our result shows lines clearly.

In the low contrast region (as shown in Figure 4), our method preserves not only the fine details but also the global tone similarity completely. In the dotted circled area which contains lots of leaves in the original image, our method results in an image that is very close to the original image, while Ostromoukhov's method shows a dim texture and the Pang and Chang methods do not represent the original image perfectly. Also, in the region indicated by the arrows in Figure 4, Pang's method makes visual artifacts such as vertical stripes in the mid-tone area which do not exist in the original image, but our method doesn't make them because we added Gaussian noise to the thresholds. Therefore, we can say that our method preserves the fine textures and reduces the visual artifacts simultaneously. Also, our method operates robustly in the low contrast region.

4. CONCLUSION

We have presented a very efficient Laplacian based structure-aware error diffusion algorithm. Although quite simple in the key idea of our algorithm that use Laplacian information in thresholds, our algorithm shows quite good performance preserving structural similarity as well as tone similarity. At the same time, it is fast and simple. Our algorithm can overcome the drawbacks of the original error diffusion in the uniform region and the textured region. It especially reduces the drawbacks of former error diffusion methods in the low contrast region. In comparisons with state-of-the-art error diffusions, our algorithm results in visually excellent image quality and involves computational simplicity.

5. REFERENCES

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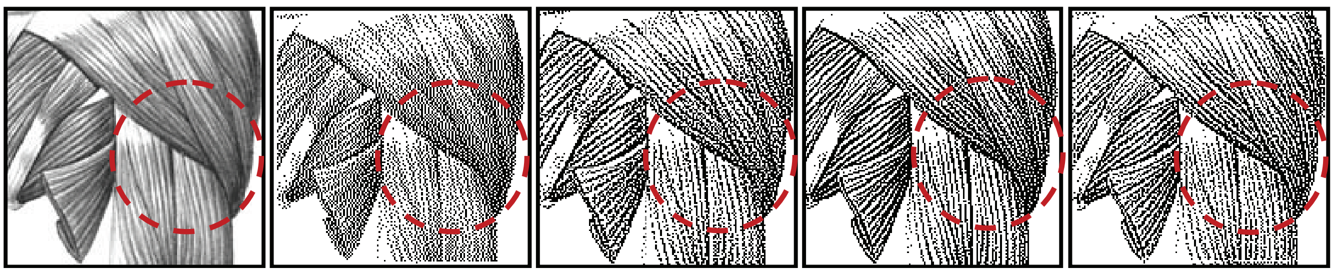
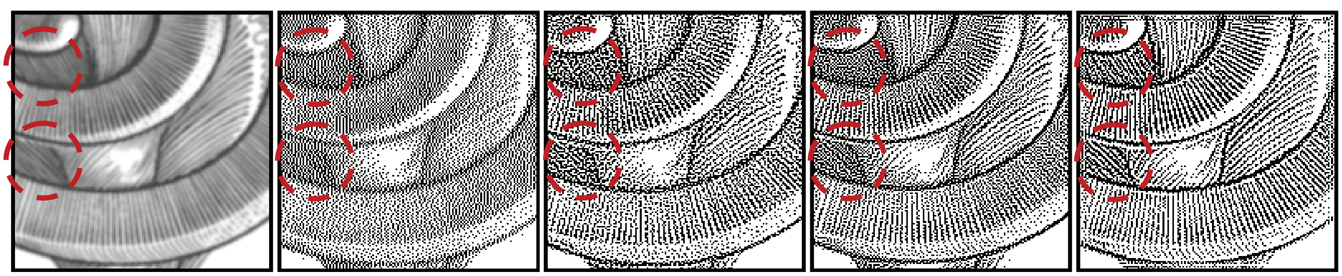


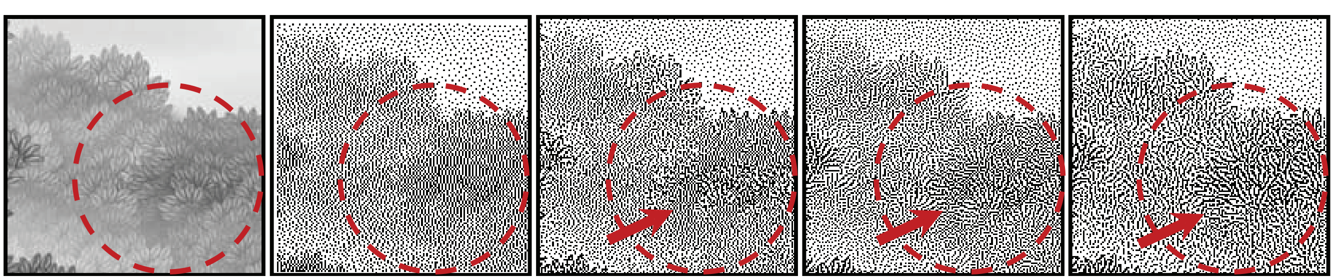
(a) (b) (c) (d) (e)

Figure 2. "Arm" Image. (a) Original image. (b) Ostromoukhov's method. (c) Pang's method. (d) Chang's method. (e) Our method. All of the image resolutions are 150 × 150 pixels.



(a) (b) (c) (d) (e)

Figure 3. "Snail" Image. (a) Original image. (b) Ostromoukhov's method. (c) Pang's method. (d) Chang's method. (e) Our method. All image resolution is 150 × 150.



(a) (b) (c) (d) (e)

Figure 4. "Bush" Image. (a) Original image. (b) Ostromoukhov's method. (c) Pang's method. (d) Chang's method. (e) Our method. All image resolution is 160 × 160.