Embedding Halftones of Different Resolutions in a Full-Scale Halftone

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***Abstract*—To efficiently render halftone images for various printers and displays that support different resolutions, it is desirable that all halftoning results can be produced at a time, and all of them can be embedded in a single full-scale halftone image such that a simple down-sampling process can extract images of suitable resolutions from it if necessary. This letter presents a framework for achieving this objective with multiscale error diffusion. A multi-resolution halftoning algorithm is proposed based on this framework. Simulation results show that the proposed algorithm can provide good image quality at different resolutions.**

***Index Terms*—Constrained halftoning (CH), halftoning, multiscale error diffusion (MED), multiscale processing, scalable media.**

I. Introduction

DIGITAL halftoning is a process of converting a continuous-tone image to black and white dots for its reproduction with a bilevel output device. There are many algorithms for digital halftoning [1]–[3], and nowadays, the most popular approach is error diffusion, as it provides good image quality at a reasonable cost.

When one renders halftone images for different printers of different resolutions, it is desirable that the output can be scalable in a way that it embeds low-resolution halftone images into a full-scale halftone image and, through a very simple procedure such as down-sampling, the low-resolution halftone images can be obtained from the high-resolution halftone image directly. This so-called multi-resolution halftoning issue was first addressed by Wong [4]. To achieve this objective, Wong deals with it as a constrained halftoning (CH) problem.

In general, a CH problem can be solved as follows. First, a halftone of lower resolution, say, I, is generated by whatever means. This image then defines the down-sampled pixels of the halftone of higher resolution to be generated. In the generation of the halftone of higher resolution, pixels are processed in a predefined order with error diffusion. When the pixel encountered corresponds to a pixel of the halftone of lower resolution, say, $I_{(i,j)}$, after down-sampling, its output value is assigned to be the binary value of $I_{(i,j)}$. Otherwise, it is determined by the thresholding result of the quantizer as usual. In either case, the error is then diffused with a causal filter. For the sake of reference, those pixels whose values are determined by the halftone image of lower resolution instead of the thresholding result of the quantizer during error diffusion are referred to as constrained pixels in this letter.

This CH framework can work with any conventional error diffusion algorithms that process pixels in a predefined scanning order, producing scalable halftone images of different quality. However, since pixels are processed one by one according to a predefined order and this framework does not take a constrained pixel into account until the pixel is encountered in the course, it is very likely that the value assigned to a constrained pixel is against the natural result of thresholding. This mismatch disturbs the harmony of a local region and degrades the quality of the output. In [5], Wong successfully reduces this problem by using an adaptive error diffusion filter. However, as we shall see in the analysis result to be presented later, pattern artifacts and directional hysteresis still exist due to the causal nature of the error diffusion filter used in this approach.

Multiscale error diffusion (MED) is a recently proposed halftoning technique, and it was proven to be superior to conventional error diffusion, as it can eliminate directional hysteresis completely [6]. We found that, due to its frame-based nature, it could be modified to realize CH easily and effectively. In this letter, we propose a framework for generating scalable halftone images with various MED algorithms such as [6]–[8]. The proposed approach takes care of the constrained pixels well before handling the unconstrained pixels. This allows one to compensate for the disturbance caused by the mismatch in the dot assignment of constrained pixels when handling the unconstrained pixels. Based on this framework, we proposed an algorithm in which a modified version of a recently proposed MED algorithm [8] is used. Analysis results showed that it achieved the best performance as compared with other multi-resolution halftoning algorithms.

II. Proposed Framework for Generating Scalable Halftones With MED Algorithms

Suppose one wants to halftone a continuous-tone image X. Without loss of generality, we assume that X is of size $N \times N$ and X^r, the downscaled version of X, is of size $(N/s_r) \times (N/s_r)$, where $s_r \in \{2^r | r = 1, 2, \ldots, R; 2^R < 2^L = N\}$ is a desirable scaling factor. Note that this combination of N and s_r is picked for illustration only. In general, N and s_r can be any integer values, and the framework presented here can be easily modified to handle it.

The objective is to produce an output such that all B^r can be obtained by simply down-sampling B, where B and B^r are, respectively, the halftone results of X and X^r. Note that X can

Manuscript received June 20, 2005; revised October 5, 2005. This work was supported by the Research Grants Council of the Hong Kong Special Administrative Region under Grant PolyU 5205/04E. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Dipti Prasad Mukherjee.

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Digital Object Identifier 10.1109/LSP.2005.862605

be down-scaled with any approach to obtain X^r, producing different results. In this letter, X^r is obtained by averaging X as follows:

$$X^r_{(i,j)} = \frac{1}{s_r \times s_r}\left(\sum_{m=0}^{s_r-1}\sum_{n=0}^{s_r-1} X_{(s_r i+m, s_r j+n)}\right) \quad \text{for } i,j = 0,1,\ldots,\left(\frac{N}{s_r}\right)-1 \quad (1)$$

where $X^r_{(i,j)}$ and $X_{(i,j)}$ are, respectively, the (i,j)th pixels of X^r and X.

In the proposed framework, starting with $r = R$, we iteratively generate B^r with X^r and then use B^r as a constraint to produce B^{r-1} in the next iteration until B is eventually obtained. As selected by the user, B^R is of the lowest resolution to be supported in the scalable B. There is no constraint to generate it, and one can exploit any MED algorithms [6]–[8] by setting the input image to be X^R.

To obtain B^r with X^r for $0 < r < R$, the same MED algorithm can be applied by applying a constraint in the initialization stage of generating B^r. Suppose one has already obtained B^r with X^r and starts to produce B^{r-1} with X^{r-1}. At the very beginning, we force the down-sampled elements of B^{r-1} to be

$$B^{r-1}_{(m,n)} = B^r_{(i,j)} \quad \text{if } (m,n) = (2i,2j) \quad \text{for } i,j = 0,1,\ldots,\left(\frac{N}{s_r}\right)-1 \quad (2)$$

where $B^r_{(i,j)}$ is the (i,j)th element of B^r, and $B^{r-1}_{(m,n)}$ is the (m,n)th element of B^{r-1}. Note that assignment (2) guarantees that B^r can be obtained by simply down-sampling B^{r-1}.

X^{r-1} is then updated by (3), shown at the bottom of the page, where $X^{r-1}_{(m,n)}$ is the (m,n)th pixel of X^{r-1}, and W is defined as $W = [W_{(-1,-1)}W_{(-1,0)}W_{(-1,1)}; W_{(0,-1)}W_{(0,0)}W_{(0,1)}; W_{(1,-1)}W_{(1,0)}W_{(1,1)}] = [1,2,1; 2,-12,2; 1,2,1]/12$. To handle corner or boundary pixels, W is modified, and filters such as [0,0,0;0,−5,2;0,2,1]/5 and [0,0,0;2,−8,2;1,2,1]/8 are used instead to avoid energy leakage. After updating X^{r-1}, the remaining unprocessed pixels are processed with the selected MED algorithm as usual to produce B^{r-1}.

Note that this framework handles all constrained pixels before processing those nonconstrained pixels. Besides, unlike CH, it does not confine the direction of error diffusion and hence provides more flexibility to compensate for the negative effect of assignment (2), in which a constrained pixel is assigned a value without concerning its original intensity. As a result, an output of higher image quality can be obtained.

III. Performance Analysis

Though the proposed framework works with any MED algorithms, we found that not every MED algorithm could provide a good performance in multi-resolution halftoning. To look for a good multi-resolution halftoning algorithm, an analysis was carried out to evaluate the impact of various error diffusion algorithms in constrained halftoning. In the analysis, multi-resolution halftoning was applied to a constant gray-level image of size 128 × 128 with various error diffusion algorithms, and the dot distribution in their outputs was studied. Directional distribution function $D_{r_1,r_2}(\alpha)$ is a useful tool to study dot distribution in a halftone [1]. In $D_{r_1,r_2}(\alpha)$, inner radius r_1 and outer radius r_2 define a ring region for analysis, and angular parameter α indexes a particular segment in the region. Note that $D_{r_1,r_2}(\alpha) > 1$ and $D_{r_1,r_2}(\alpha) < 1$, respectively, indicate a favoring and an inhibition of dots in direction α. In the ideal case, we have $D_{r_1,r_2}(\alpha) = 1$ for all α, which indicates an isotropic distribution in the output. In our analysis, the annular ring is defined by $r_1 = 0$ and $r_2 = 3$, and it is divided into 16 equal segments.

Figs. 1(ia)–(c) show some multi-resolution halftoning results when the gray level is 31/255, and Figs. 1(iia)–(c) show their corresponding down-sampling results. In particular, Fig. 1(ia) shows the result of using framework CH and standard error diffusion [3] (CH-SED), while Fig. 1(ib) shows the result of [5] (CH-AED), which actually exploits framework CH and adaptive error diffusion. There exist directional ripples in Figs. 1(ia) and (ib). Fig. 1(ic) shows the case of using the proposed constrained halftoning framework for MED algorithms with the MED algorithm proposed in [6] ($\mathrm{CH_p}$-MED). It is visually smoother, but pattern artifacts can be observed.

Figs. 1(iiia)–(c) show the directional distribution functions of Figs. 1(ia)–(c). One can see that all outputs suffer from directional hysteresis, and dots are not uniformly distributed in all directions. For CH-SED and CH-AED, this is expected because of the reasons mentioned in Section I. As for $\mathrm{CH_p}$-MED, though theoretically directional hysteresis can be eliminated by MED, it appears again after CH. The fixed error diffusion filter exploited in [6] diffuses quantization error to the constrained pixels, and this amount of error is trapped there forever. $\mathrm{CH_p}$-MED does not take care of the constrained pixels well in the course, and error leakage happens in every constrained pixel.

To solve the problem encountered in $\mathrm{CH_p}$-MED, an adaptive diffusion filter should be used to avoid diffusing error back to the constrained pixels. In this letter, we suggest using a modified version of the feature-preserving MED algorithm proposed in [8]. The algorithm proposed in [8] detects whether white or black dots are minority dots in a local region and then assigns a minority dot to the region so as to preserve the local feature. In

$$X^{r-1}_{(2i+p,2j+q)} = \begin{cases} 0, & \text{if}(p,q) = (0,0) \\ X^{r-1}_{(2i+p,2j+q)} + W_{(p,q)}\left(X^{r-1}_{(2i,2j)} - B^{r-1}_{(2i,2j)}\right), & \text{if}(p,q) \in \{(u,v)|u,v = 0,\pm 1\} \setminus \{(0,0)\} \end{cases} \quad \text{for each constrained pixel } (i,j) \quad (3)$$

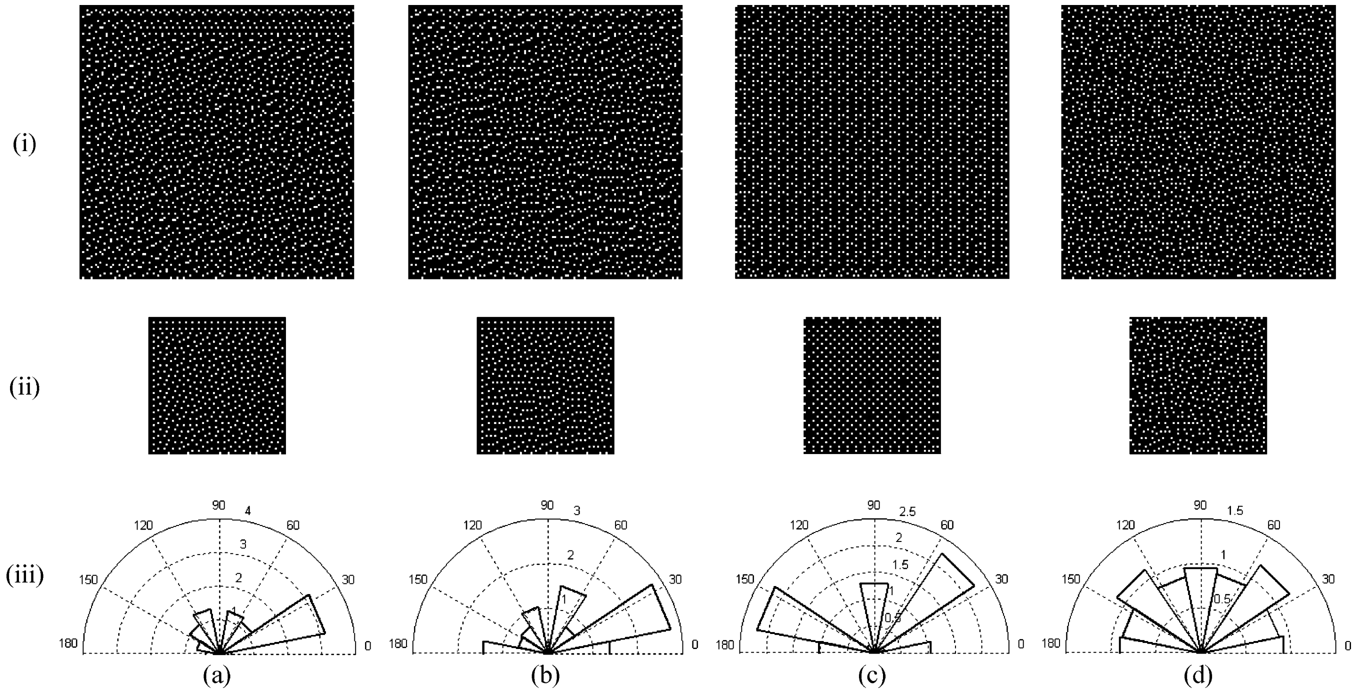

Fig. 1. Halftoning results of (a) CH-SED, (b) CH-AED, (c) $\mathrm{CH_P}$-MED, and (d) the proposed algorithm for constant gray-level input (31/255) of size 128 × 128. (i) Full-scale outputs. (ii) Down-sampling results of (i). (iii) Directional distributions.

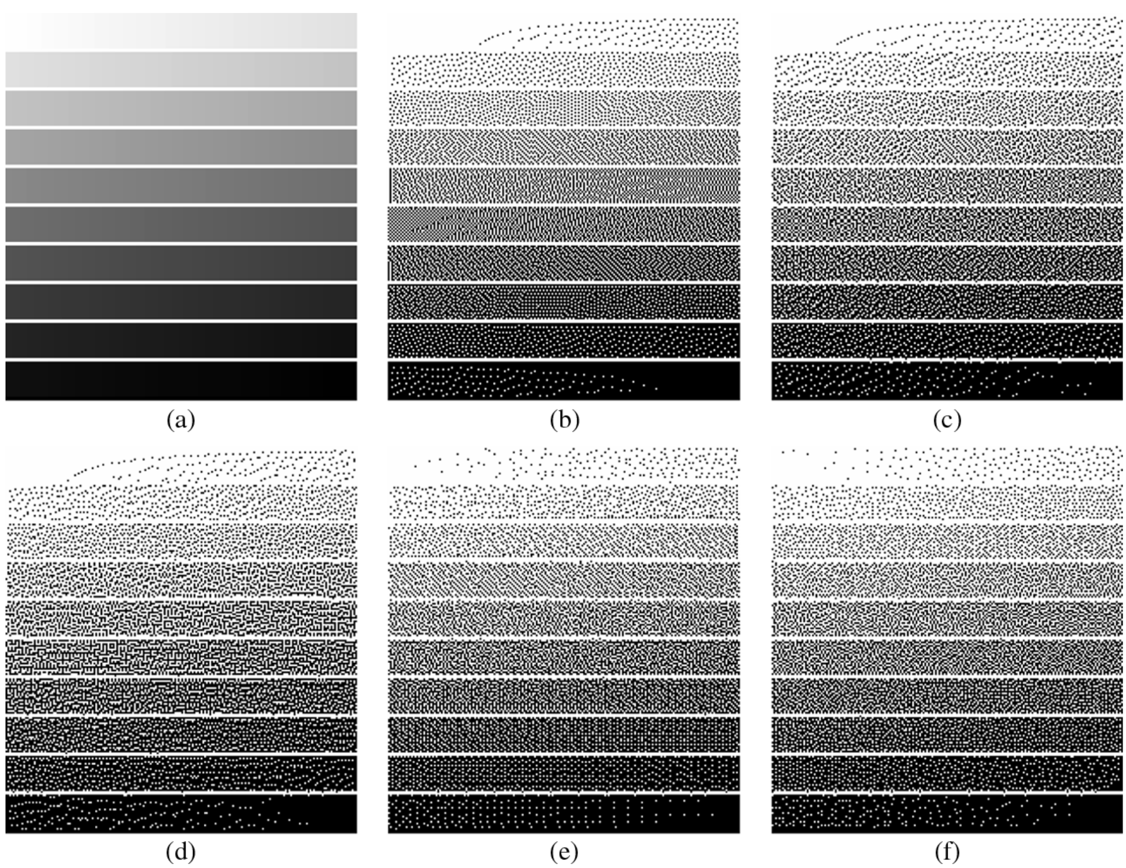

Fig. 2. (a) Original ramp image and halftone results of (b) [3], (c) CH-SED, (d) CH-AED, (e) $\mathrm{CH_P}$-MED, and (f) the proposed algorithm.

CH, when generating the halftoning result of higher resolution, constrained pixels are handled first without concerning any local feature. After that, the critical pixel positions in the region for displaying the local feature may have already been occupied by constrained pixels. Even though the feature-preserving mechanism of this algorithm is activated, there is not much gain in the quality, and sometimes it may even make it worse. Hence, when this MED algorithm [8] works with CH in our suggested multi-resolution halftoning algorithm $(\mathrm{CH_P} - \mathrm{MED_P})$, this feature-preserving mechanism is purposely off. Accordingly, no

TABLE I
SUMMARY OF THE ALGORITHMS EVALUATED FOR COMPARISON

Algorithm	Scanning order	Error diffusion filter	Constrained halftoning
SED [3]	Raster	Non-adaptive, causal	No
CH-SED	Raster	Non-adaptive, causal	Scheme in Section I
CH-AED [5]	Raster	Adaptive, causal	Scheme in Section I
CH_p-MED	Max intensity guidance [6]	Non-adaptive, non-causal	Scheme in Section II
Proposed	Max intensity guidance[1]	Adaptive, non-causal	Scheme in Section II

[1] The scheme used in [8] without turning the feature preserving mechanism on

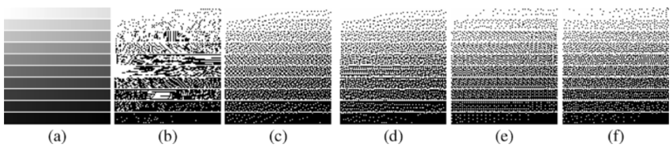

Fig. 3. Down-sampling results of Figs. 2(a)–2(f).

region-oriented detection of minority dots is performed, and it always locates the minority dots of the whole image. Table I contrasts the differences among the algorithms evaluated in the analysis.

Fig. 1(id) shows the full-scale halftoning result of the proposed algorithm, and Fig. 1(iid) shows its down-sampling result. There is no directional hysteresis and little, if any, pattern artifact in both images. The directional distribution function shown in Fig. 1(iiid) also verifies that dots are evenly distributed in all directions.

IV. SIMULATION RESULTS

Simulation has been carried out to evaluate the performance of various multi-resolution halftoning algorithms. Fig. 2(a) shows the original testing ramp image of size 200×218, and Fig. 3(a) is its down-sampling result. As shown in Figs. 2(b) and 3(b), a plain conventional halftoning algorithm such as standard error diffusion [3] does not embed a low-resolution halftoning result into its output, and hence, the down-sampling result of its output can be very poor. Figs. 2(c)–2(f) show, respectively, the corresponding multi-resolution halftoning results of using CH-SED, CH-AED, CH_p-MED, and the proposed algorithm. Figs. 3(a)–3(f) are the down-sampling results of Figs. 2(a)–2(f). A down-sampling factor of 2 was applied to each direction. In the realization of CH_p-MED and the proposed algorithm, R was selected to be 2. The performance of the proposed algorithm is the best in terms of directional hysteresis and pattern noise.

Fig. 4 shows the performance of various algorithms in terms of the directional distribution of dots in their halftoning results of different constant gray-level inputs. The performance is measured in terms of the variance of $(1 - D_{0,\max(\lambda,3)}(\alpha))$ for all α, where λ is the principle wavelength of the input gray level. Logarithmic scale is used for the abscissa in the plots. The plots show that the proposed algorithm outperforms the other approaches.

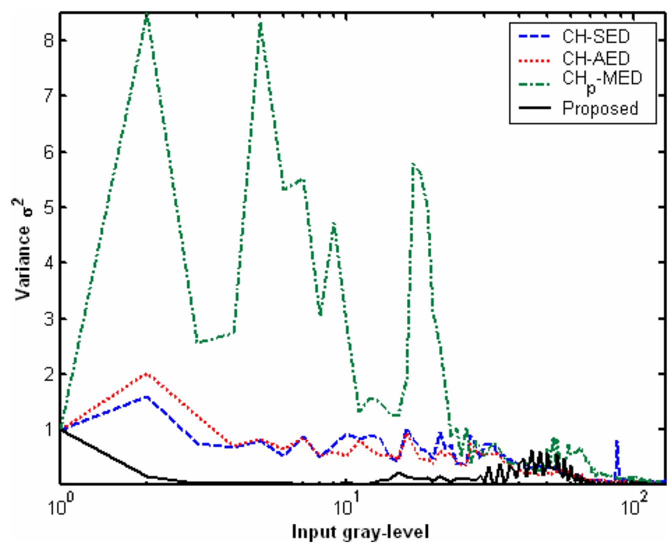

Fig. 4. Performance of the full-scaled outputs in terms of directional distribution of dots.

V. CONCLUSION

In this letter, we proposed a CH framework for MED algorithms to realize multi-resolution halftoning. Based on this framework, we proposed a multi-resolution halftoning algorithm for producing scalable halftone images. Given a monochrome image, the algorithm produces a set of halftoning results of different resolution and embeds those of lower resolution into the full-scale one such that they can be extracted by direct down-sampling. Simulation results show that the proposed algorithm can provide good halftoning results at different resolutions. Some critical factors for achieving good constrained halftoning results are also discussed in this letter.

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