2.3.5 HALFTONING

- Used for representation of continuous-tone with devices that are bi-level, or which can generate more than two output levels but not a sufficient number of levels to prevent the appearance of quantization artifacts.
- All halftoning techniques rely on a local spatial average over binary textures by the human viewer to create the impression of continuous-tone.
- Detail is rendered by locally modulating these textures.

Units for Gray-Value (Ideal)

Texture							
Digital Value	255	191	127	63	0		
Absorptance	0.0	0.25	0.5	0.75	1.0		
Reflectance/ Transmittance	1.0	0.75	0.5	0.25	0.0		

Notation

 $0 \le f[m,n] \le 1$, digital, continuous-tone original image

g[m,n] = 0, 1, digital halftone image

g(x,y) – displayed/printed halftone image

Model for Printed/Displayed Images

$$g(x,y) = \sum_{m} \sum_{n} g[m,n]p_{S}(x - mR, y - nR)$$

- device-addressable points lie on a square lattice with interval R × R
- $p_s(x,y)$ printed/displayed spot profile
- if there is spot overlap, it is assumed to be additive.

Halftoning Techniques

- 1. Binarization with a constant threshold
- 2. Pattern printing
- 3. Screening
- 4. Error diffusion

Binarization with a Constant Threshold

g[m,n] =
$$\begin{cases} 1, & f[m,n] \ge 0.5 \\ 0, & else \end{cases}$$

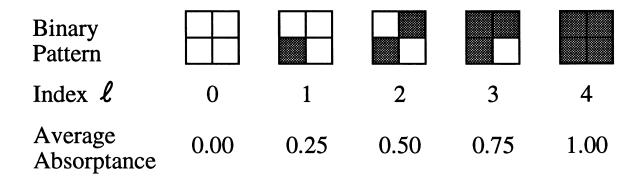
minimizes mean-squared error

$$E = \sum_{m} \sum_{n} |f[m,n] - g[m,n]|^2$$

does not yield acceptable quality

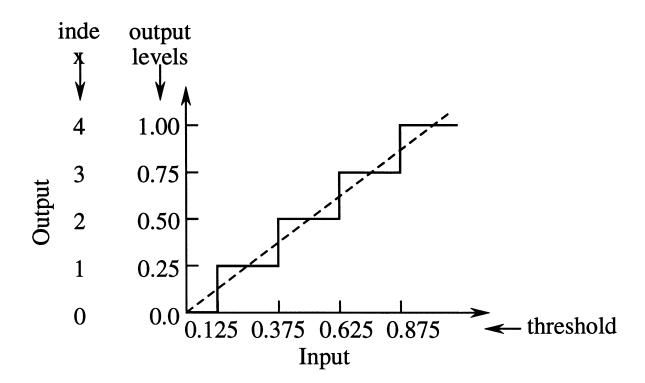
PATTERN PRINTING

• pattern library p[m,n;ℓ]



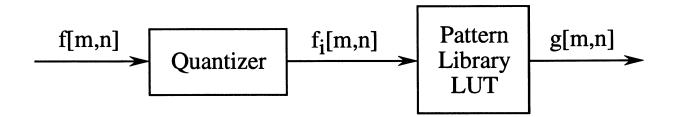
• $M \times N$ patterns yield MN + 1 output quantization levels (Here M = N = 2).

• quantizer design



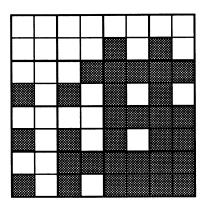
Mapping to index image

$$f_i[m,n] = \emptyset: [\emptyset - 1/2]/MN < f[m,n] \le [\emptyset + 1/2]/MN$$



0.1	0.1	0.3	0.3
0.2	0.4	0.7	0.7
0.2	0.3	0.7	0.9
0.3	0.7	0.9	0.9

0	0	1	1
1	2	3	3
1	1	3	4
1	3	4	4



f[m,n]

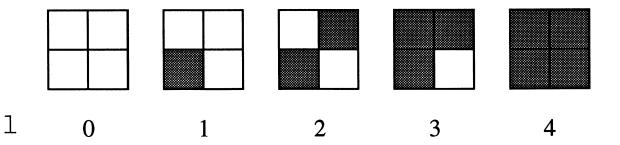
 $f_i[m,n]$

g[m,n]

- Halftone image is larger than continuous-tone original by factor M × N.
- If device resolution is sufficiently high, pattern printing will yield acceptable results.
- At lower resolution, images appear blocky and lack detail.
- There is a tradeoff between detail resolution and number of quantization levels.

Alternate Representations for Pattern Library

• Dot profile function p[m,n;ℓ]



Index matrix

3	2
1	1

to binary structureStacking constraint must be satisfied

- Entries indicate order in which dots are added

Stacking Constraint

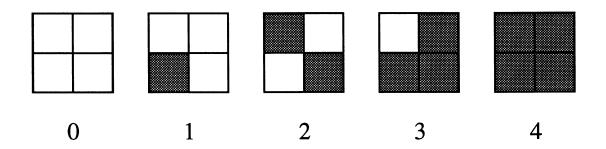
For any $0 \le \emptyset \le MN$,

$$p[m,n;\ell] = 1 \implies p[m,n;k] = 1 \quad \forall k \ge \ell$$

or

$$p[m,n;\ell] = 0 \implies p[m,n;\ell] = 0 \quad \forall k \le \ell$$

• A dot profile that does not satisfy this constraint:



Alternate Representations for Pattern Library (cont.)

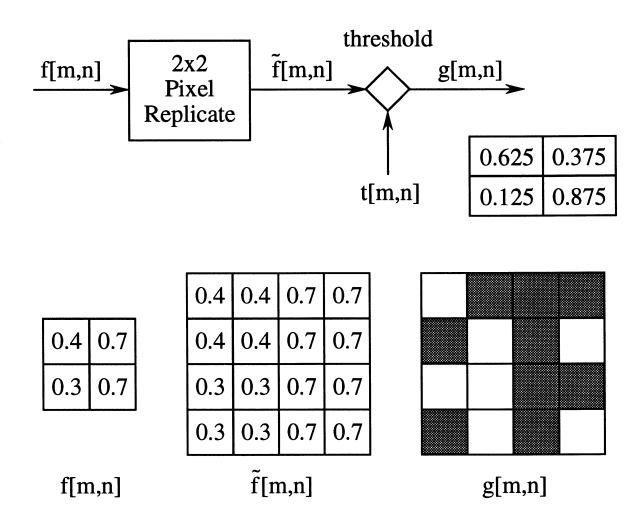
• Index matrix i[m,n]

3	2
1	4

• Threshold Matrix t[m,n] t[m,n]=(i[m,n] - 0.5)/MN

0.625	0.375
0.125	0.875

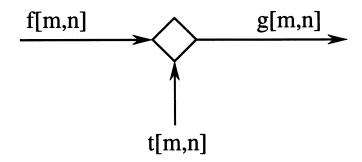
Alternate Implementation for Pattern Printing



• threshold signal is doubly periodic

$$t[m,n] = t[m + kM, n + \emptyset N]$$

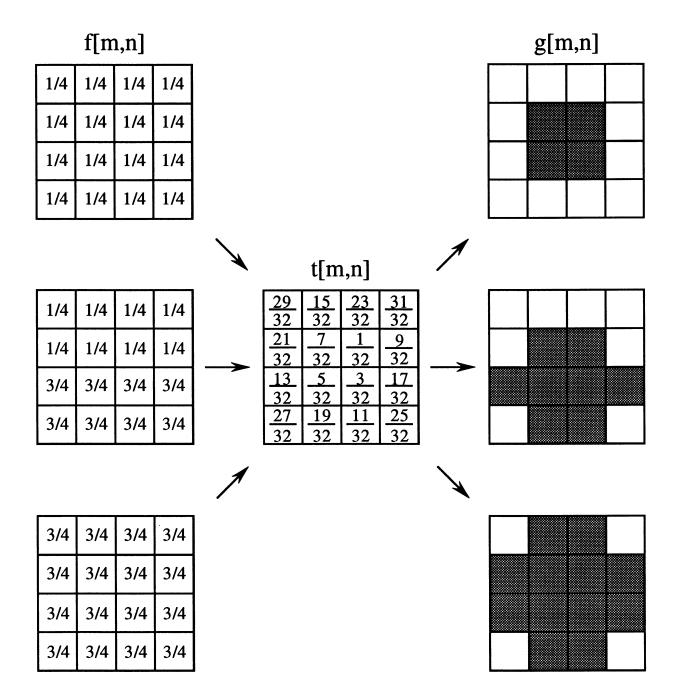
SCREENING



$$g[m,n] = \begin{cases} 1, & f[m,n] \ge t[m,n] \\ 0, & else \end{cases}$$

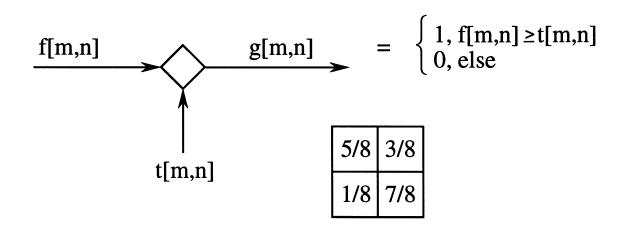
- Halftone image is same size as continuous-tone original image.
- Technique is equivalent to photographic contact screening process traditionally used in graphic arts and printing.
- Dot profile function must satisfy stacking constraint.
- Screening achieves better detail rendition than pattern printing via partial dotting property.

Partial Dotting



Different Representations for Screening

1. Spatially varying threshold



2. Addition of dither signal

3. Point-to-Point Nonlinear Mapping Via Dot Profile Function

- $p[m + kM, n + \emptyset N; b] = p[m,n;b]$
- g[m,n] = p[m,n; f[m,n]]

Choice of Threshold Matrix (Screen Function)

- Size of matrix (M and N) determines period of screen and number of quantization levels.
- Thresholds are chosen to yield correct tone reproduction (minimum quantization error).
- Spatial arrangement of the thresholds determines characteristics of the texture that results.

Recall Dual Representation

Index Matrix

Threshold Matrix

3	2
1	4

i[m,n]

t[m,n]=(i[m,n] - 0.5)/MN

Clustered Dot Screen

63	58	49	37	38	50	59	64
57	48	36	22	23	39	51	60
47	35	21	11	12	24	40	52
34	20	10	4	1	5	13	25
33	19	9	3	2	6	14	26
46	32	18	8	7	15	27	41
56	45	31	17	16	28	42	53
62	55	44	30	29	43	54	61

i[m,n]

• Consecutive thresholds are located in close spatial proximity.

Properties of Clustered Dot Screen

- 1. Relatively visible texture
- 2. Relatively poor detail rendition
- 3. Uniform texture across entire grayscale
- 4. Robust performance with non-ideal output devices
 - non-additive spot overlap
 - spot-to-spot variability
 - noise

Dispersed Dot Screen

Bayer's Optimum Index Matrix (1973)

Recursive Definition (Judice, Jarvis, Ninke, 1974)

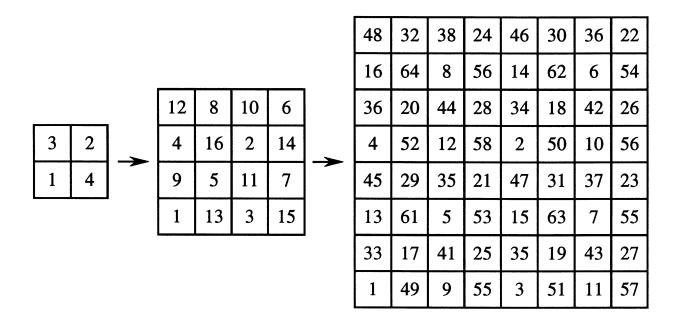
- 1. Let i'[m,n] be any $M \times N$ index matrix
- 2. Define a new $2M \times 2N$ index matrix i[m,n] as

$$\begin{bmatrix} 4(i^{'}[m,n]-1)+3 & | & 4(i^{'}[m,n]-1)+2 \\ ----- & | & ----- \\ 4(i^{'}[m,n]-1)+1 & | & 4(i^{'}[m,n]-1)+4 \end{bmatrix}$$

$$i[m,n]$$

3. Recursively generate $2^K \times 2^K$ matrix starting with 1×1 index matrix [1].

Example



• Consecutive threshold are located far apart spatially.

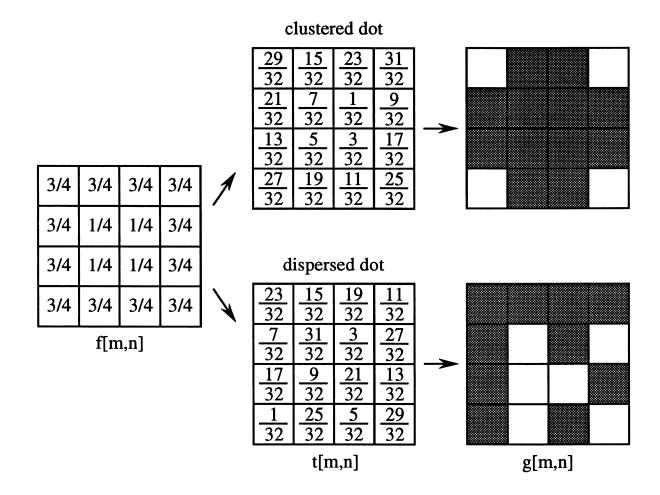
Recursive Definition for Threshold Matrix

$$\begin{bmatrix} t'[m,n] + \frac{0.5}{4MN} & t'[m,n] - \frac{0.5}{4MN} \\ ---- & | ---- \\ t'[m,n] - \frac{1.5}{4MN} & t'[m,n] + \frac{1.5}{4MN} \end{bmatrix}$$

$$t[m,n]$$

- Yields finer amplitude quantization over larger (2M × 2N) area.
- Retains good detail rendition within smaller $M \times N$ regions.

Example illustrating improved detail rendition with a dispersed dot screen



Properties of Dispersed Dot Screen

- 1. Within any region containing K dots, the K thresholds should be distributed as uniformly as possible between 0 and 1.
- 2. Textures used to represent individual gray levels have low visibility.
- 3. Improved detail rendition.
- 4. Transition between textures corresponding to different gray levels may be more visible.
- 5. Poor performance with non-ideal output devices

FOURIER ANALYSIS

1. Screening

Continuous-tone, continuous-parameter original image

$$f(x,y) \overset{CSFT}{\longleftrightarrow} F(u,v)$$
$$f[m,n] = f(mR, nR)$$

• Halftone image

$$g(x,y) \leftrightarrow G(u,v)$$

$$g(x,y) = \sum_{m} \sum_{n} g[m,n] p_{s}(x-mR, y-nR)$$

$$CSFT$$

$$p_{s}(x,y) \leftrightarrow P_{s}(u,v)$$

Definition of Transforms

Continuous-space Fourier transform (CSFT)

$$F(u,v) = \iint f(x,y)e^{-j2\pi(ux+vy)}dxdy$$

• Discrete Fourier transform (DFT)

$$P[k, \emptyset; b] = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} p[m, n; b] e^{-j2\pi(\frac{mk}{M} + \frac{n^{0}}{N})}$$

• Dot profile function (M × N period)

$$p[m,n;b] \leftrightarrow P[k,\emptyset;b]$$

$$g[m,n] = p[m,n; f[m,n]]$$

• Halftone cell - $X \times Y$ X = MR, Y = NR

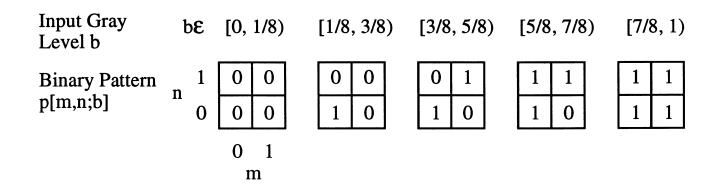
Spectrum of Halftone Image

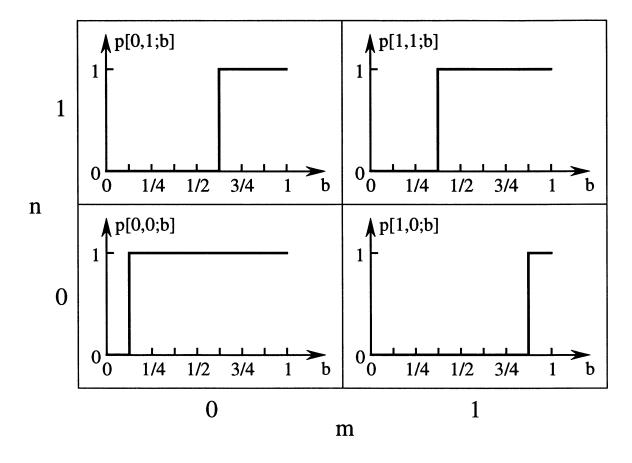
$$G(u,v) = P_s(u,v) \sum_{m} \sum_{n} F_{mn}(u-m/X, v-n/Y)$$

$$F_{mn}(u,v) = CSFT\{f_{mn}(x,y)\}$$

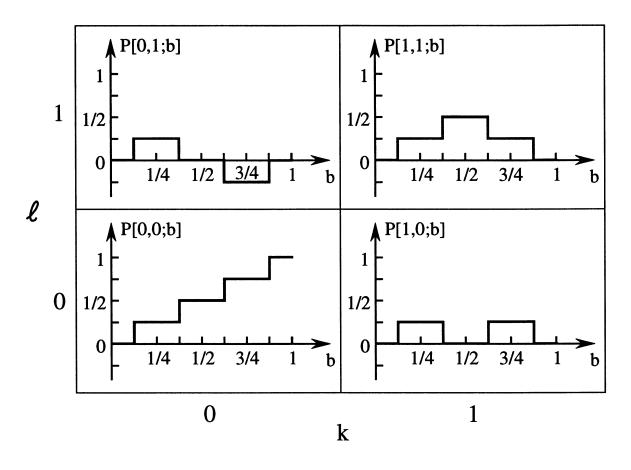
$$f_{mn}(x,y) = P[m,n; f(x,y)]$$

Relation Between Dot Profile and Spectral Nonlinearities





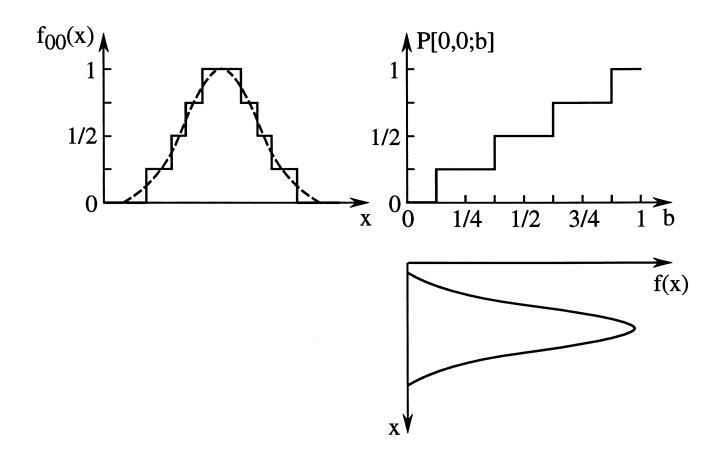
Input Gray Level b		[0, 1/8)	[1/8, 3/8)	[3/8, 5/8)	[5/8, 7/8)	[7/8, 1)
DFT P[k, ℓ ;b]	$\ell \begin{bmatrix} 1 \\ 0 \end{bmatrix}$	0 0 0	1/4 1/4 1/4 1/4	0 1/2 1/2 0	1/4 1/4 3/4 1/4	0 0 1 0
		0 1 k				

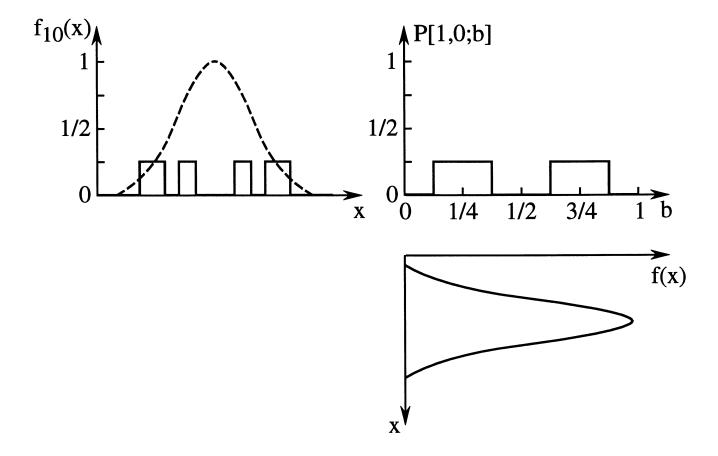


Nonlinearly Transformed Images

$$f_{mn}(x,y) = P[m,n;f(x,y)]$$

1-D Example





2. Pattern Printing

• Continuous-tone, continuous-parameter original image

$$f(x,y) \stackrel{CSFT}{\leftrightarrow} F(u,v)$$

- Halftone cell $X \times Y$, X = MR, Y = NR
- Sample-and-hold image

$$\tilde{f}(x,y) = rect\left[\frac{x}{X}, \frac{y}{X}\right] ** comb_{XY}[f(x,y)]$$

$$\tilde{F}(u, v) = \text{sinc}(Xu, Yv) \text{ rep } \frac{1}{X} \frac{1}{Y} [F(u, v)]$$

• In analysis of screening, replace f(x,y) by $\tilde{f}(x,y)$ and F(u,v) by $\tilde{F}(u,v)$.

Other Screen Functions

- Optimized Threshold Matrices (Allebach and Stradling, 1979)
- Angled Screens (Holladay, 1980)
- Macroscreens

ERROR DIFFUSION

Definition of terms

- Continuous-tone, discrete parameter, original image f[m,n]
- Modified continuous-tone image f[m,n]
- Diffusion weights $w[k, \emptyset]$

$$w[k, \ell] \ge 0$$
, $\sum_{k} \sum_{\ell} w[k, \ell] = 1$

• Halftone image - g[m,n]

Description of algorithm

- Start with $\tilde{f}[m,n] \equiv f[m,n]$
- Scan pixels in image in a predetermined order, and carry out following computations

threshold

$$g[m,n] = \begin{cases} 1, & \tilde{f}[m,n] \ge 0.5 \\ 0, & \text{else} \end{cases}$$

compute error

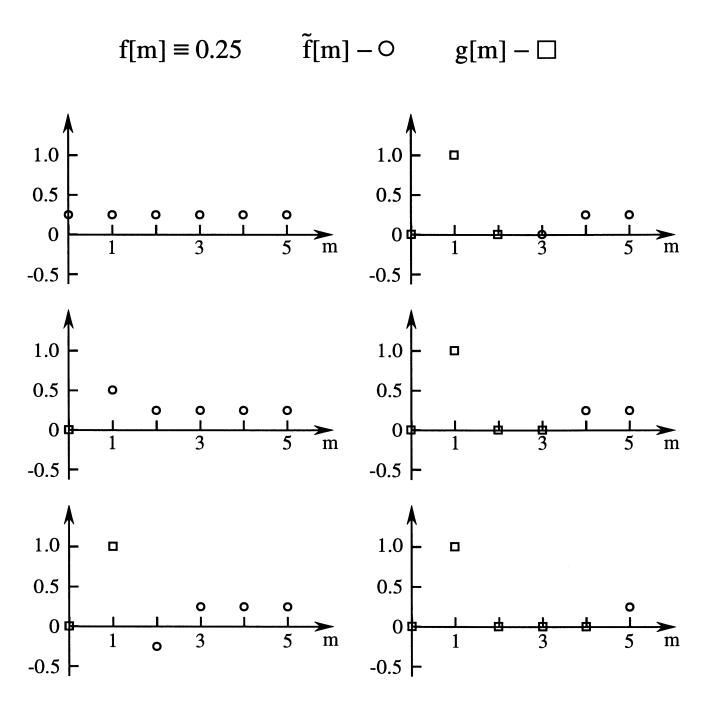
$$e[m,n] = g[m,n] - \tilde{f}[m,n]$$

diffuse error

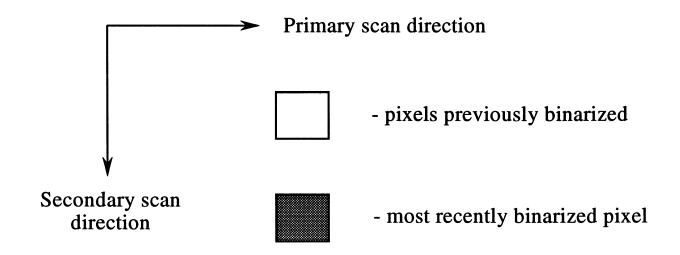
$$\tilde{f}[m+k, n+\emptyset] = \tilde{f}[m+k, n+\emptyset] - w[k, \emptyset] e[m,n]$$

 $(m+k, n+\emptyset) \in \{\text{pixels not yet binarized}\}$

1-D Example



2-D Error Diffusion Weighting Filters



		7/16
3/16	5/16	1/16

Floyd, and Steinberg (1976)

			7/48	5/48
3/48	5/48	7/48	5/48	3/48
1/48	3/48	5/48	3/48	1/48

Jarvis, Judice, and Ninke (1976)

Characteristics of Error Diffusion

- At each step, error diffusion preserves local average over part of image that has been binarized and part that is yet to be binarized.
- No fixed number of quantization levels.
- Requires more computation than screening.
- Excellent detail rendition (sharpens image).
- Generally good texture with some exceptions:
 - texture contouring
 - worm-like patterns
 - texture used to render a given gray level is context-dependent

FOURIER ANALYSIS (Knox, 1991)

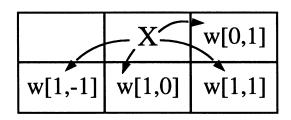
Two Views of Error Diffusion

1. Diffuse error immediately after binarizing pixel to all pixels in neighborhood

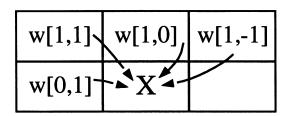
$$g[m,n] = \begin{cases} 1, & \tilde{f}[m,n] \ge 0.5 \\ 0, & \text{else} \end{cases}$$

$$e[m,n] = g[m,n] - \tilde{f}[m,n]$$

$$\tilde{f}[m+k, n+\ell] = \tilde{f}[m+k, n+\ell] - w[k,\ell]e[m,n]$$



2. Diffuse error from all neighboring pixels to pixel to be binarized, just prior to binarization



$$\tilde{\mathbf{f}}[\mathbf{m},\mathbf{n}] = \mathbf{f}[\mathbf{m},\mathbf{n}] - \sum_{\mathbf{k}} \sum_{\mathbf{k}} \mathbf{w}[\mathbf{k},\mathbf{k}] \mathbf{e}[\mathbf{m} - \mathbf{k}, \mathbf{n} - \mathbf{k}]$$
 (1)

$$g[m,n] = \begin{cases} 1 , & \tilde{f}[m,n] \ge 0.5 \\ 0 , & \text{else} \end{cases}$$
 (2)

$$e[m,n] = g[m,n] - \tilde{f}[m,n]$$
 (3)

Recursive Expression for the Error Image

Combine Eqs. (1) and (2)

$$e[m,n] = g[m,n] - f[m,n] + \sum_{k} \sum_{\ell} w[k,\ell] e[m-k, n-\ell]$$

Discrete-Space Fourier Transform (DSFT)

$$E(\mu,\nu) = \sum_{m} \sum_{n} e[m,n]e^{-j(m\mu+n\nu)}$$

$$E(\mu,\nu) = G(\mu,\nu) - F(\mu,\nu) + W(\mu,\nu)E(\mu,\nu)$$

- We would like an expression for $G(\mu, \nu)$ in terms of $F(\mu, \nu)$
- Instead, we have

$$G(\mu, \nu) = F(\mu, \nu) + \overline{W}(\mu, \nu)E(\mu, \nu)$$

• High-pass filter

$$\overline{W}(\mu, \nu) = 1 - W(\mu, \nu)$$

• Error spectrum is not known

$$E(\mu, \nu) = G(\mu, \nu) - \tilde{F}(\mu, \nu)$$

Error Model

$$E(\mu, \nu) = cF(\mu, \nu) + R(\mu, \nu)$$

 Original image component cF(μ,ν); constant c depends on weighting and input image

weighting	c
1-D	0.0
Floyd and Steinberg	0.55
Jarvis, Judice,	0.80
and Ninke	

• Residual $R(\mu, \nu)$ - may still be image dependent

Edge-Enhancing Property of Error Diffusion

Combine

$$G(\mu,\nu) = G(\mu,\nu) + \overline{W}(\mu,\nu)E(\mu,\nu) \quad \text{and}$$

$$E(\mu,\nu) = cF(\mu,\nu) + R(\mu,\nu)$$

$$G(\mu,\nu) = [1+c\overline{W}(\mu,\nu)]F(\mu,\nu) + \overline{W}(\mu,\nu)R(\mu,\nu)$$

- Edge-Enhancing Filter $1 + c\overline{W}(\mu, \nu)$
- Blue Noise $\overline{W}(\mu, \nu)R(\mu, \nu)$