

Ph.D. Defense

# Analysis and Design of Vector Error Diffusion Systems for Image Halftoning

*Niranjan Damera-Venkata*

Embedded Signal Processing Laboratory

The University of Texas at Austin

Austin TX 78712-1084

## Committee Members

Prof. Ross Baldick

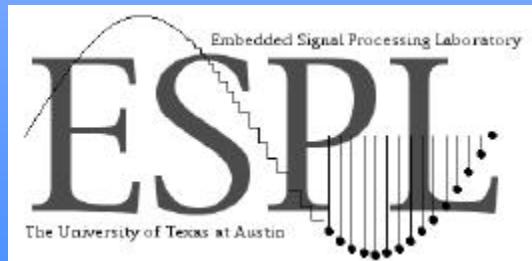
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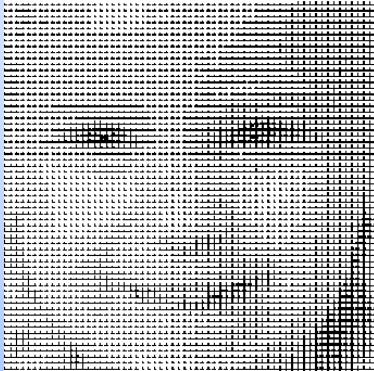
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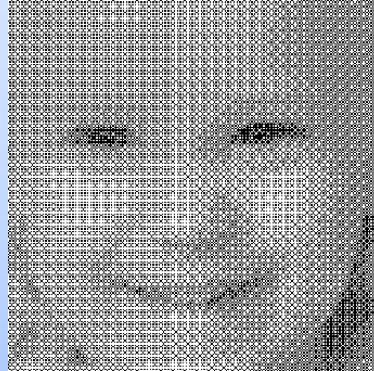
# Outline

- **Digital halftoning**
  - Grayscale error diffusion halftoning
  - Color error diffusion halftoning
- ***Contribution #1: Matrix gain model for color error diffusion***
- ***Contribution #2: Design of color error diffusion systems***
- ***Contribution #3: Block error diffusion***
  - Clustered-dot error diffusion halftoning
  - Embedded multiresolution halftoning
- **Contributions**

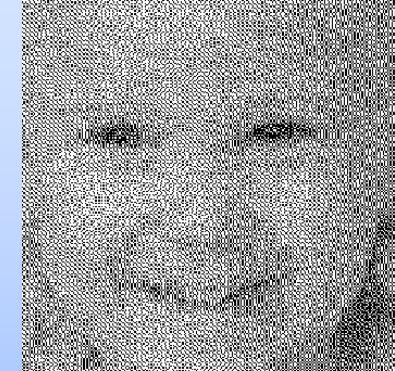
# Digital Halftoning



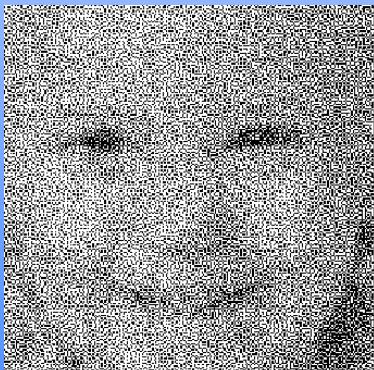
Cluttered Dot Dither  
*AM Halftoning*



Dispersed Dot Dither  
*FM Halftoning*



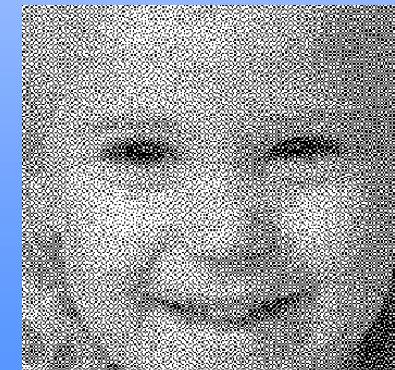
Error Diffusion  
*FM Halftoning 1975*



Blue-noise Mask  
*FM Halftoning 1993*



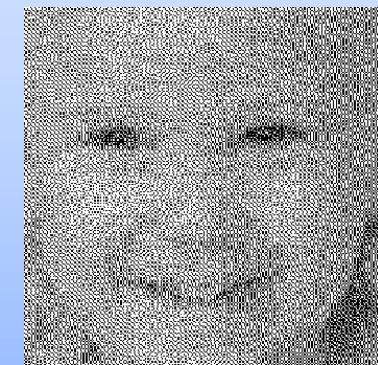
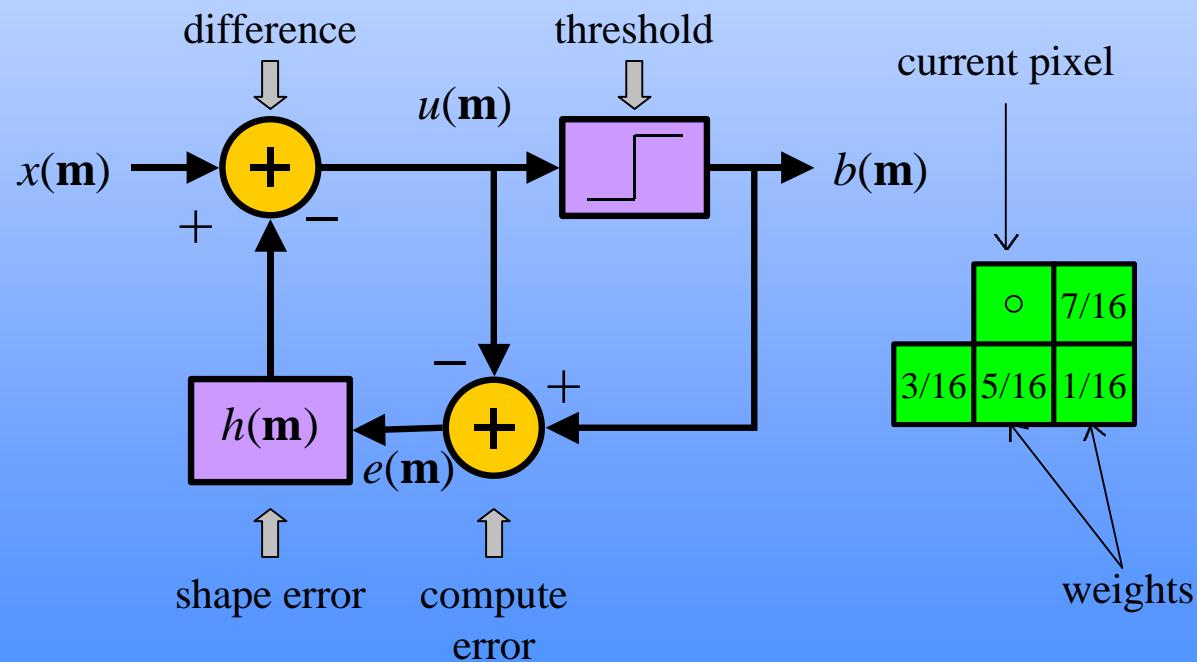
Green-noise Halftoning  
*AM-FM Halftoning 1992*



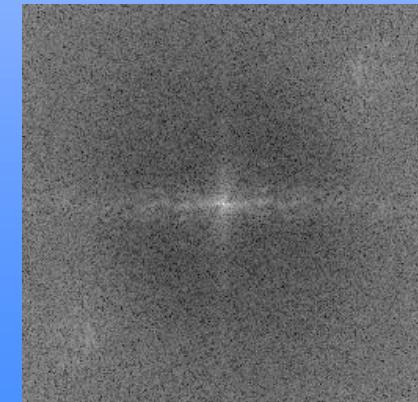
Direct Binary Search  
*FM Halftoning 1992*

# Grayscale Error Diffusion

- Shape quantization noise into high frequencies
- Two-dimensional sigma-delta modulation
- Design of error filter is key to high quality



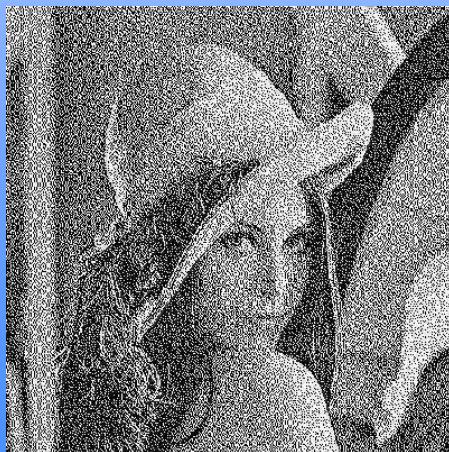
Error Diffusion



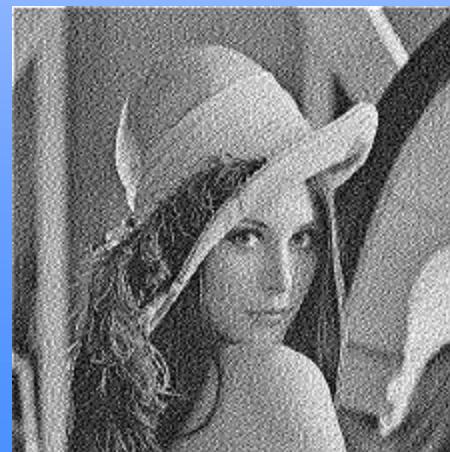
Spectrum

# Modeling Grayscale Error Diffusion

- Sharpening is caused by a correlated error image [Knox, 1992]



Error images



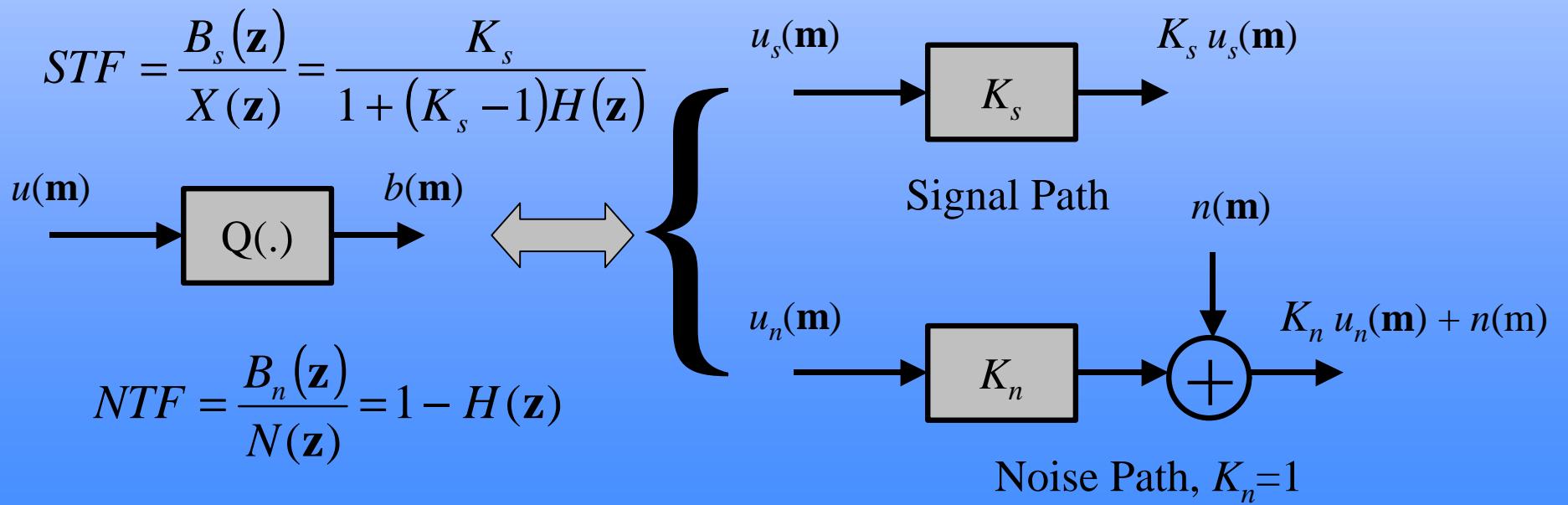
Halftones

Floyd-  
Steinberg

Jarvis

# Modeling Grayscale Error Diffusion

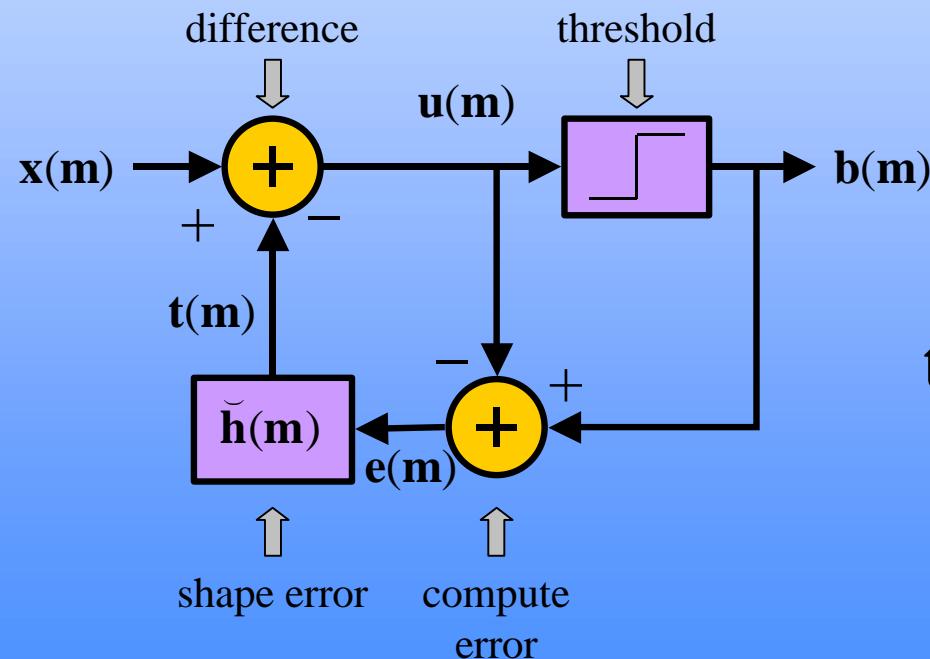
- Apply sigma-delta modulation analysis to two dimensions
  - Linear gain model for quantizer in 1-D [Ardalan and Paulos, 1988]
  - Linear gain model for grayscale image [Kite, Evans, Bovik, 2000]
  - Signal transfer function (STF) and noise transfer function (NTF)
  - $1 - H(z)$  is highpass so  $H(z)$  is lowpass



# Vector Color Error Diffusion

- Error filter has matrix-valued coefficients
- Algorithm for adapting matrix coefficients

[Akaran, Yardimci, Cetin 1997]



$$t(m) = \sum_{k \in \delta} \underbrace{\tilde{h}(k)}_{\text{matrix}} \underbrace{e(m - k)}_{\text{vector}}$$

# Color Error Diffusion

- **Open issues**

- Modeling of color error diffusion in the frequency domain
- Designing robust fixed matrix-valued error filters
- Efficient implementation
- Linear model for the human visual system for color images

- **Contributions**

- “Matrix gain model” for linearizing color error diffusion
- Model-based error filter design
- Parallel implementation of the error filter as a filter bank

Contribution #1:

## The Matrix Gain Model

- Replace scalar gain with a matrix

$$\breve{\mathbf{K}}_s = \arg \min_{\breve{\mathbf{A}}} E \left[ \left\| \mathbf{b}(\mathbf{m}) - \breve{\mathbf{A}} \mathbf{u}(\mathbf{m}) \right\|^2 \right] = \breve{\mathbf{C}}_{\mathbf{bu}} \breve{\mathbf{C}}_{\mathbf{uu}}^{-1}$$

$$\breve{\mathbf{K}}_n = \breve{\mathbf{I}}$$

$\mathbf{u}(\mathbf{m})$  quantizer input  
 $\mathbf{b}(\mathbf{m})$  quantizer output

- Noise is uncorrelated with signal component of quantizer input
- Convolution becomes matrix–vector multiplication in frequency domain

$$\mathbf{B}_n(\mathbf{z}) = (\breve{\mathbf{I}} - \breve{\mathbf{H}}(\mathbf{z})) \mathbf{N}(\mathbf{z})$$

Noise component of output

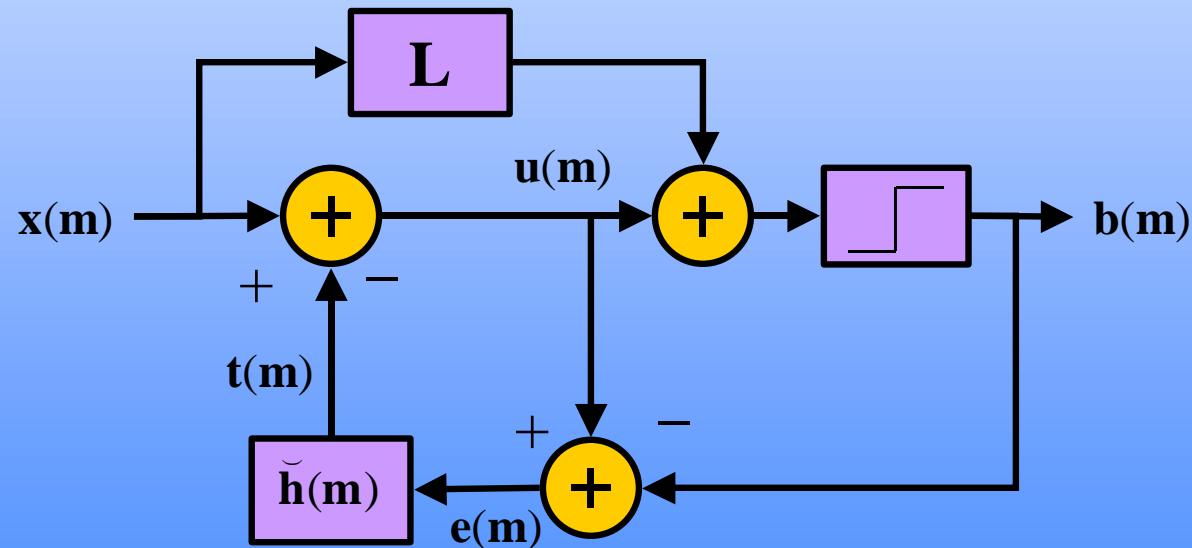
$$\mathbf{B}_s(\mathbf{z}) = \breve{\mathbf{K}} (\breve{\mathbf{I}} + \breve{\mathbf{H}}(\mathbf{z}) (\breve{\mathbf{K}} - \breve{\mathbf{I}}))^{-1} \mathbf{X}(\mathbf{z})$$

Signal component of output

### Contribution #1: Matrix Gain Model

## How to Construct an Undistorted Halftone

- Pre-filter with inverse of signal transfer function to obtain undistorted halftone  $\breve{G}(z) = [\breve{I} + \breve{H}(z)(\breve{K} - \breve{I})]\breve{K}^{-1}$
- Pre-filtering is equivalent to the following when  $\breve{L} = \breve{K}^{-1} - \breve{I}$

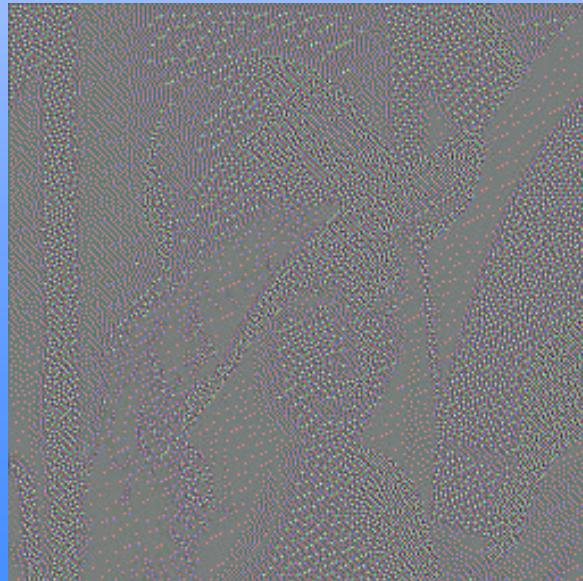


Modified error diffusion

### Contribution #1: Matrix Gain Model

## Validation #1 by Constructing Undistorted Halftone

- Generate linearly undistorted halftone
- Subtract original image from halftone
- Since halftone should be “undistorted”, the residual should be uncorrelated with the original

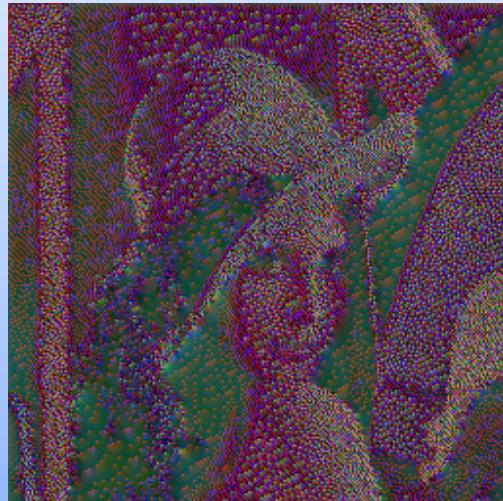


Correlation matrix of residual image (undistorted halftone minus input image) with the input image

$$\check{\mathbf{C}}_{rx} = \begin{pmatrix} 0.0006 & 0.0097 & 0.0020 \\ 0.0013 & 0.0114 & 0.0073 \\ 0.0044 & 0.0024 & 0.0043 \end{pmatrix}$$

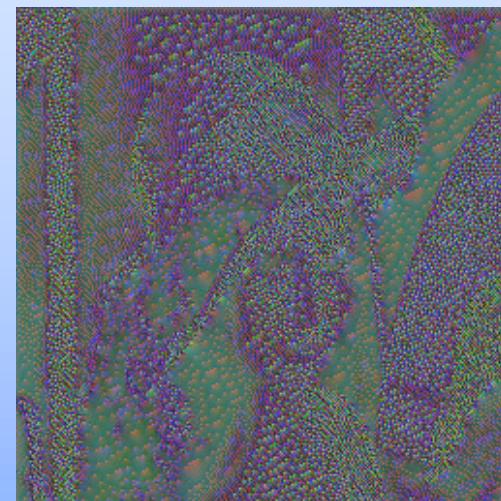
Contribution #1: Matrix Gain Model

## Validation #2 by Knox's Conjecture



Correlation matrix for an error image and input image for an error diffused halftone

$$\check{\mathbf{C}}_{\text{ex}} = \begin{pmatrix} 0.3664 & 0.0019 & 0.1778 \\ 0.2661 & 0.2348 & 0.1817 \\ 0.2173 & 0.1839 & 0.1816 \end{pmatrix}$$



Correlation matrix for an error image and input image for an undistorted halftone

$$\check{\mathbf{C}}_{\text{ex}} = \begin{pmatrix} 0.0485 & 0.0839 & 0.0082 \\ 0.0153 & 0.0550 & 0.0229 \\ 0.0160 & 0.0004 & 0.0247 \end{pmatrix}$$

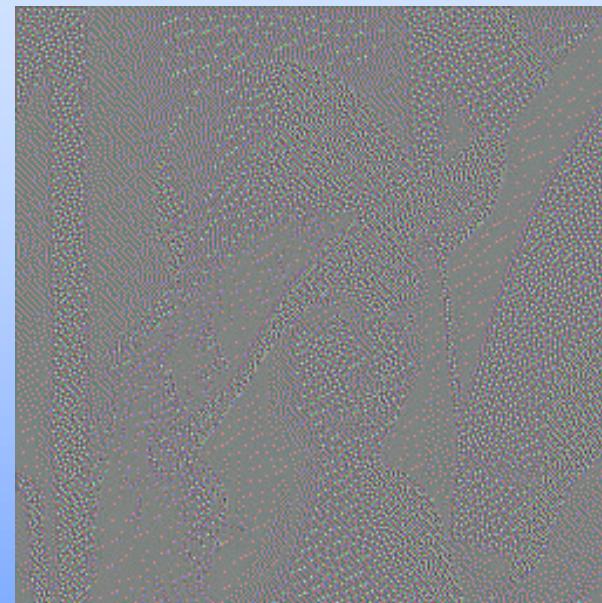
$$\mathbf{E}_s(\mathbf{z}) = 0$$

$$\mathbf{E}_n(\mathbf{z}) = \mathbf{N}(\mathbf{z})$$

### Contribution #1: Matrix Gain Model

## Validation #3 by Distorting Original Image

- Validation by constructing a linearly distorted original
  - Pass original image through error diffusion with matrix gain substituted for quantizer
  - Subtract resulting color image from color halftone
  - Residual should be shaped uncorrelated noise



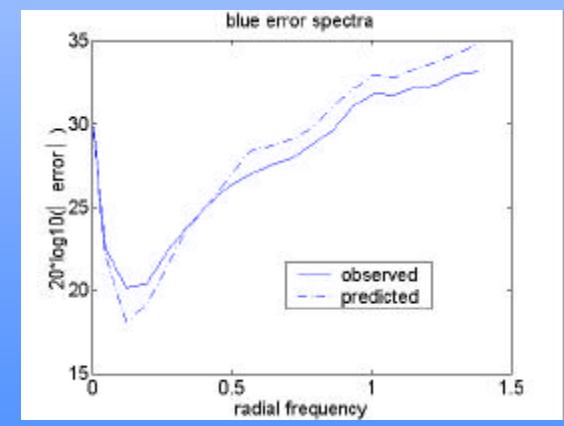
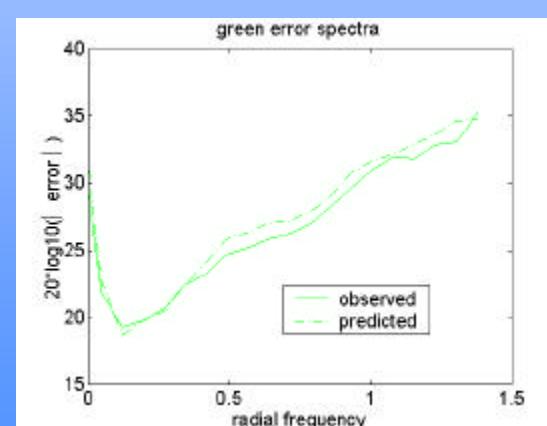
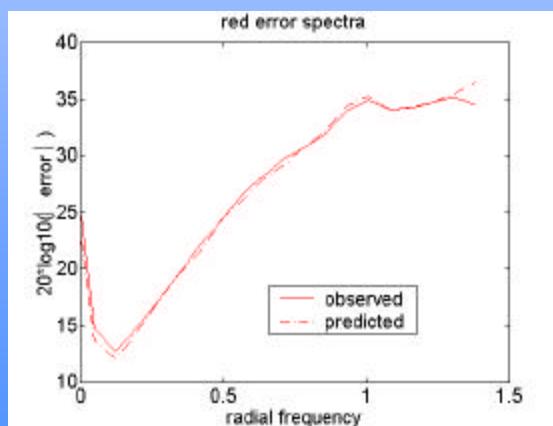
Correlation matrix of residual image (halftone minus distorted input image) with the input image

$$\breve{\mathbf{C}}_{rx} = \begin{pmatrix} 0.0012 & 0.0140 & 0.0004 \\ 0.0007 & 0.0057 & 0.0126 \\ 0.0015 & 0.0101 & 0.0056 \end{pmatrix}$$

Contribution #1: Matrix Gain Model

## Validation #4 by Noise Shaping

- Noise process is error image for an undistorted halftone
- Use model noise transfer function to compute noise spectrum
- Subtract original image from modeled halftone and compute actual noise spectrum



## Contribution #2

# Designing of the Error Filter

- Eliminate linear distortion filtering before error diffusion
- Optimize error filter  $h(m)$  for noise shaping

$$\min E[\|\mathbf{b}_n(\mathbf{m})\|^2] = E[\|\check{\mathbf{v}}(\mathbf{m}) * (\check{\mathbf{I}} - \check{\mathbf{h}}(\mathbf{m})) * \mathbf{n}(\mathbf{m})\|^2]$$

Subject to diffusion constraints

$$\left( \sum_{\mathbf{m}} \check{\mathbf{h}}(\mathbf{m}) \right) \mathbf{1} = \mathbf{1}$$

where

$\check{\mathbf{v}}(\mathbf{m})$  linear model of human visual system  
\* matrix-valued convolution

Contribution #2: Error Filter Design

## Generalized Optimum Solution

- Differentiate scalar objective function for visual noise shaping with respect to matrix-valued coefficients

$$\frac{d\left\{E\left[\left\|\mathbf{b}_n(\mathbf{m})\right\|^2\right]\right\}}{d\mathbf{h}(\mathbf{i})} = \mathbf{0} \quad \forall \mathbf{i} \in \mathcal{O}$$

- Write the norm as a trace and then differentiate the trace using identities from linear algebra  $\|\mathbf{x}\| = \text{Tr}(\mathbf{x}\mathbf{x}')$

$$\frac{d\left\{\text{Tr}(\bar{\mathbf{A}}\bar{\mathbf{X}})\right\}}{d\bar{\mathbf{X}}} = \bar{\mathbf{A}}'$$

$$\frac{d\left\{\text{Tr}(\bar{\mathbf{X}}'\bar{\mathbf{A}}\bar{\mathbf{X}}\bar{\mathbf{B}})\right\}}{d\bar{\mathbf{X}}} = \bar{\mathbf{A}}\bar{\mathbf{X}}\bar{\mathbf{B}} + \bar{\mathbf{A}}'\bar{\mathbf{X}}\bar{\mathbf{B}}'$$

$$\frac{d\left\{\text{Tr}(\bar{\mathbf{A}}\bar{\mathbf{X}}\bar{\mathbf{B}})\right\}}{d\bar{\mathbf{X}}} = \bar{\mathbf{A}}'\bar{\mathbf{B}}'$$

$$\text{Tr}(\bar{\mathbf{A}}\bar{\mathbf{B}}) = \text{Tr}(\bar{\mathbf{B}}\bar{\mathbf{A}})$$

Contribution #2: Error Filter Design

## Generalized Optimum Solution (cont.)

- Differentiating and using linearity of expectation operator give a generalization of the Yule-Walker equations

$$\sum_{\mathbf{k}} \check{\mathbf{v}}'(\mathbf{k}) \check{\mathbf{r}}_{an}(-\mathbf{i} - \mathbf{k}) = \sum_p \sum_q \sum_s \check{\mathbf{v}}'(s) \check{\mathbf{v}}(q) \check{\mathbf{h}}(p) \check{\mathbf{r}}_{nn}(-\mathbf{i} - s + p + q)$$

where

$$\mathbf{a}(\mathbf{m}) = \check{\mathbf{v}}(\mathbf{m}) * \mathbf{n}(\mathbf{m})$$

- Assuming white noise injection

$$\mathbf{r}_{nn}(\mathbf{k}) = E[\mathbf{n}(\mathbf{m}) \mathbf{n}'(\mathbf{m} + \mathbf{k})] \approx \mathbf{d}(\mathbf{k})$$

$$\mathbf{r}_{an}(\mathbf{k}) = E[\mathbf{a}(\mathbf{m}) \mathbf{n}'(\mathbf{m} + \mathbf{k})] \approx \check{\mathbf{v}}(-\mathbf{k})$$

## Contribution #2: Error Filter Design

# Generalized Optimum Solution (cont.)

- Optimum solution obtained via steepest descent algorithm

$$(\nabla J)_{(\bar{\mathbf{h}}(\mathbf{i}))} = - \sum_{\mathbf{k}} \bar{v}'(\mathbf{k}) \bar{r}_{\text{an}}(-\mathbf{i} - \mathbf{k}) + \sum_{\mathbf{p}} \sum_{\mathbf{q}} \sum_{\mathbf{s}} \bar{v}'(\mathbf{s}) \bar{v}(\mathbf{q}) \bar{h}(\mathbf{p}) \bar{r}_{\text{nn}}(-\mathbf{i} - \mathbf{s} + \mathbf{p} + \mathbf{q})$$

$$\bar{\mathbf{h}}^{(q+1)}(\mathbf{i}) = P\left(\bar{\mathbf{h}}^{(q)}(\mathbf{i}) - \mathbf{a} \left\{ (\nabla J)_{(\bar{\mathbf{h}}^{(q)}(\mathbf{i}))} \right\}\right)$$

$$P\left(\bar{\mathbf{f}}(\mathbf{i})\right) = \bar{\mathbf{f}}(\mathbf{i}) - \left( \frac{1}{3|\mathcal{S}|} \right) \left( \sum_{\mathbf{m} \in \mathcal{S}} \bar{\mathbf{f}}(\mathbf{m}) - \bar{\mathbf{I}} \right)$$

**a** - convergence rate parameter

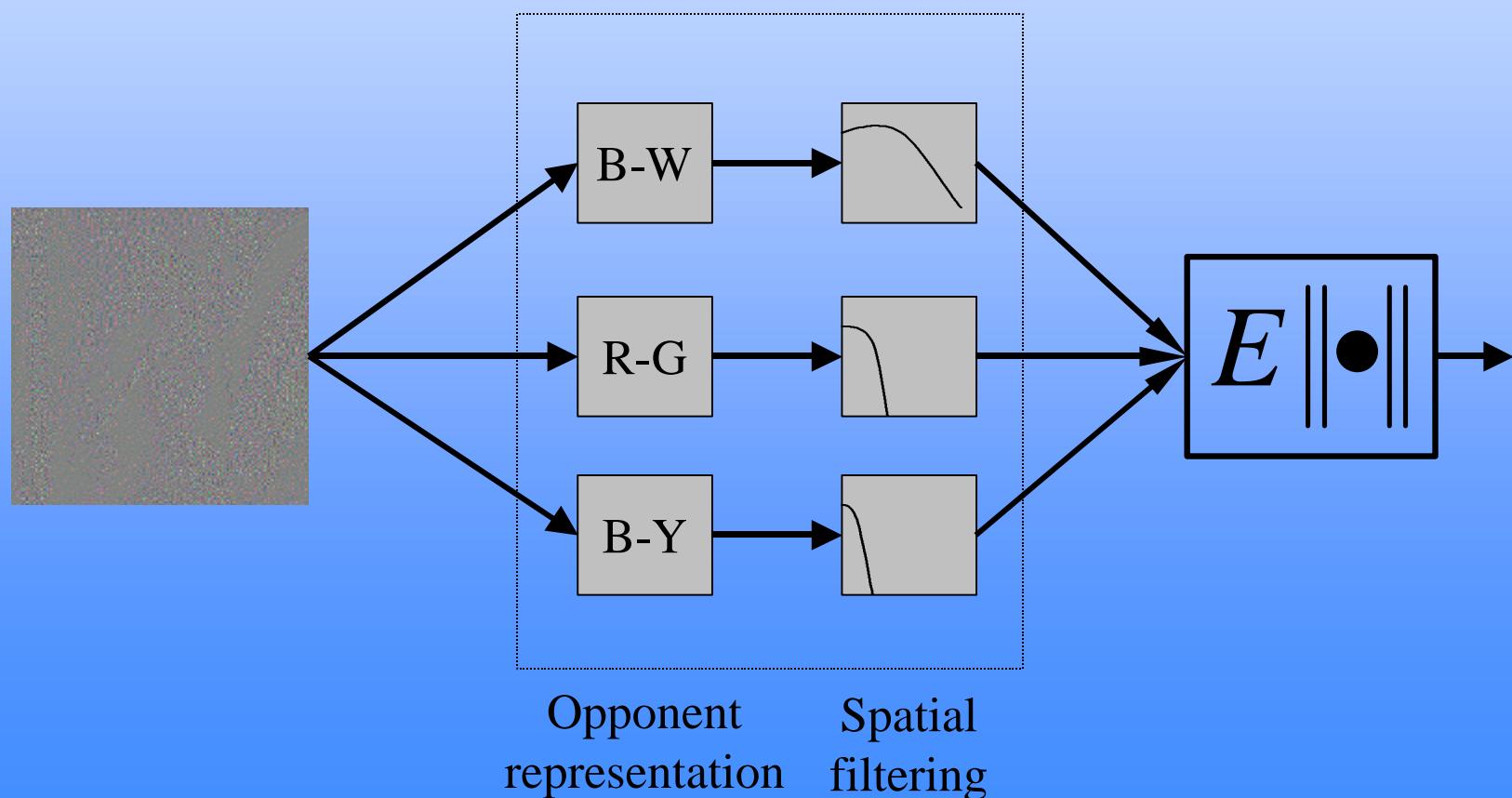
P - projection operator

**q** - iteration number

## Contribution #2: Error Filter Design

# Linear Color Vision Model

- **Pattern-Color separable model [Poirson and Wandell, 1993]**
  - Forms the basis for S-CIELab [Zhang and Wandell, 1996]
  - Pixel-based color transformation



## Linear Color Vision Model

- Undo gamma correction on RGB image
- Color separation
  - Measure power spectral distribution of RGB phosphor excitations
  - Measure absorption rates of long, medium, short (LMS) cones
  - Device dependent transformation  $C$  from RGB to LMS space
  - Transform LMS to opponent representation using  $O$
  - Color separation may be expressed as  $T = OC$
- Spatial filtering is incorporated using matrix filter  $\check{d}(m)$
- Linear color vision model  
 $\check{v}(m) = \check{d}(m)\check{T}$  where  $\check{d}(m)$  is a diagonal matrix



Floyd-Steinberg

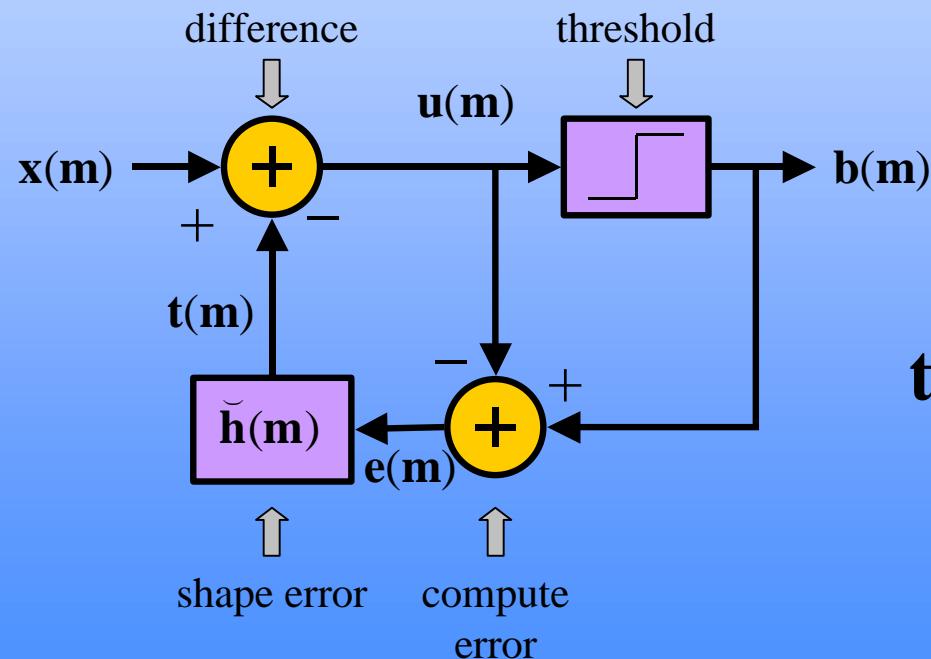


Optimum Filter

### Contribution #3

## Block Error Diffusion

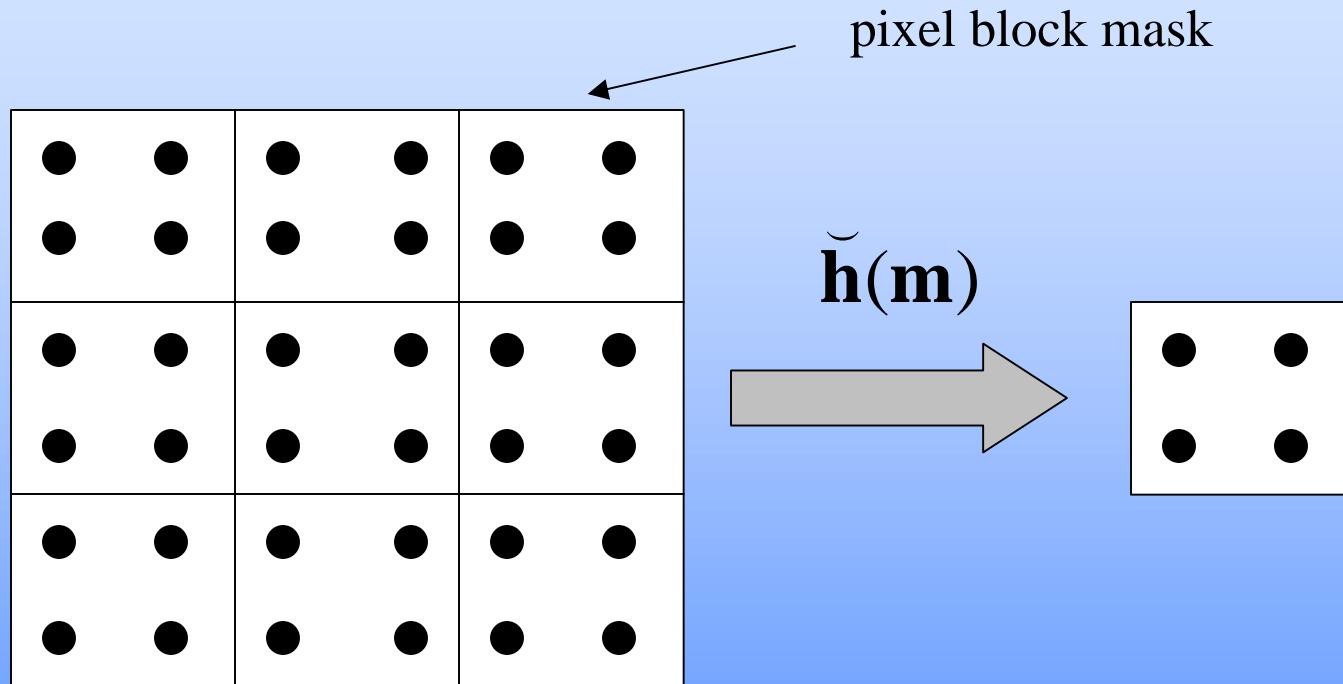
- Input grayscale image is “blocked”
- Error filter uses all samples from neighboring blocks and diffuses an error block



$$t(m) = \sum_{k \in S} \tilde{h}(k) e(m - k)$$

### Contribution #3: Block Error Diffusion

## Block Interpretation of Vector Error Diffusion



- Four linear combinations of the 36 pixels are required to compute the output pixel block

### Contribution #3: Block Error Diffusion

## Block FM Halftoning

- **Why not “block” standard error diffusion output?**
  - Spatial aliasing problem
  - Blurred appearance due to prefiltering
- **Solution**
  - Control dot shape using block error diffusion
  - Extend conventional error diffusion in a natural way
- **Extensions to block error diffusion**
  - AM-FM halftoning
  - Sharpness control
  - Multiresolution halftone embedding
  - Fast parallel implementation

Contribution #3: Block Error Diffusion

## Block FM Halftoning Error Filter Design

- Start with conventional error filter prototype

$$\tilde{\mathbf{a}} = \left[ \frac{1}{16} \quad \frac{5}{16} \quad \frac{3}{16} \quad \frac{7}{16} \right]$$

- Form block error filter as Kronecker product

$$\breve{\Gamma} = \tilde{\mathbf{a}} \otimes \breve{\mathbf{D}} \quad \quad \breve{\mathbf{D}} \text{ diffusion matrix}$$

- Satisfies “lossless” diffusion constraint

$$\breve{\Gamma}\mathbf{1} = \mathbf{1} \quad \quad \breve{\Gamma} \geq \breve{\mathbf{0}}$$

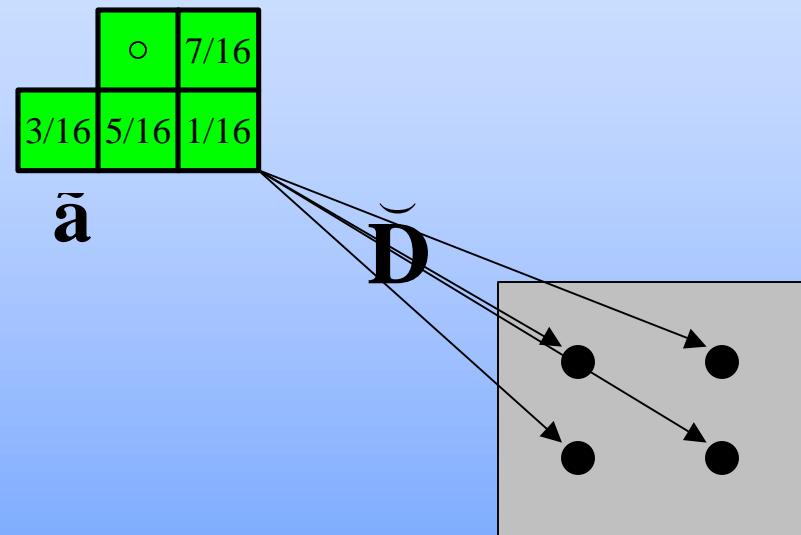
- Diffusion matrix satisfies

$$\breve{\mathbf{D}}\mathbf{1} = \mathbf{1} \quad \quad \breve{\mathbf{D}} \geq \breve{\mathbf{0}}$$

Contribution #3: Block Error Diffusion

## Block FM Halftoning Error Filter Design

- FM nature of algorithm controlled by scalar filter prototype
- Diffusion matrix decides distribution of error within a block
- In-block diffusions are constant for all blocks to preserve isotropy

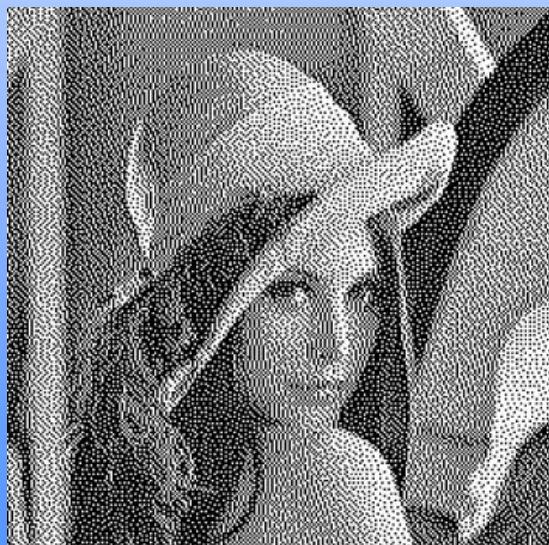


Contribution #3: Block Error Diffusion

## Block FM Halftoning Results

- Vector error diffusion with diffusion matrix

$$\check{\mathbf{D}} = \frac{1}{N^2} [\check{\mathbf{1}}] \quad N \text{ is the block size}$$



Pixel replication



Floyd-Steinberg



Jarvis

Contribution #3: Block Error Diffusion

## Block FM Halftoning with Arbitrary Shapes



Plus dots



Cross dots

### Contribution #3: Block Error Diffusion

## Embedded Multiresolution Halftoning

- Only involves designing the diffusion matrix
  - FM Halftones when downsampled are also FM halftones

LMH	H	MH	H
H	H	H	H
MH	H	MH	H
H	H	H	H

Halftone pixels at Low, Medium and High resolutions

- Error at a pixel is diffused to the pixels of the same color

Contribution #3: Block Error Diffusion

## Embedded Halftoning Results



High  
resolution  
halftone



Medium  
resolution  
halftone



Low  
resolution  
halftone



Simple  
down-  
sampling

# Contributions

- **Matrix gain model for vector color error diffusion**
  - Eliminated linear distortion by pre-filtering
  - Validated model in three other ways
- **Model based error filter design for a calibrated device**
- **Block error diffusion**
  - FM halftoning
  - AM-FM halftoning (not presented)
  - Embedded multiresolution halftoning
- **Efficient parallel implementation (not presented)**

## Published Halftoning Work Not in Dissertation

N. Damera-Venkata and B. L. Evans, ``Adaptive Threshold Modulation for Error Diffusion Halftoning," *IEEE Transactions on Image Processing*, January 2001, to appear.

T. D. Kite, N. Damera-Venkata, B. L. Evans and A. C. Bovik, "A Fast, High Quality Inverse Halftoning Algorithm for Error Diffused Halftoned images," *IEEE Transactions on Image Processing*, vol. 9, no. 9, pp. 1583-1593, September 2000.

N. Damera-Venkata, T. D. Kite , W. S. Geisler, B. L. Evans and A. C. Bovik , ``Image Quality Assessment Based on a Degradation Model" *IEEE Transactions on Image Processing*, vol. 9, no. 4, pp. 636-651, April 2000.

N. Damera-Venkata, T. D. Kite , M. Venkataraman, B. L. Evans, ``Fast Blind Inverse Halftoning" *IEEE Int. Conf. on Image Processing*, vol. 2, pp. 64-68, Oct. 4-7, 1998.

T. D. Kite, N. Damera-Venkata, B. L. Evans and A. C. Bovik, "A High Quality, Fast Inverse Halftoning Algorithm for Error Diffused Halftoned images," *IEEE Int. Conf. on Image Processing*, vol. 2, pp. 64-68, Oct. 4-7, 1998.

## Submitted Halftoning Work in Dissertation

N. Damera-Venkata and B. L. Evans, ``Matrix Gain Model for Vector Color Error Diffusion," *IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing*, June 3-5, 2001, to appear.

N. Damera-Venkata and B. L. Evans, ``Design and Analysis of Vector Color Error Diffusion Systems," *IEEE Transactions on Image Processing*, submitted.

N. Damera-Venkata and B. L. Evans, ``Clustered-dot FM Halftoning Via Block Error Diffusion," *IEEE Transactions on Image Processing*, submitted.

# Types of Halftoning Algorithms

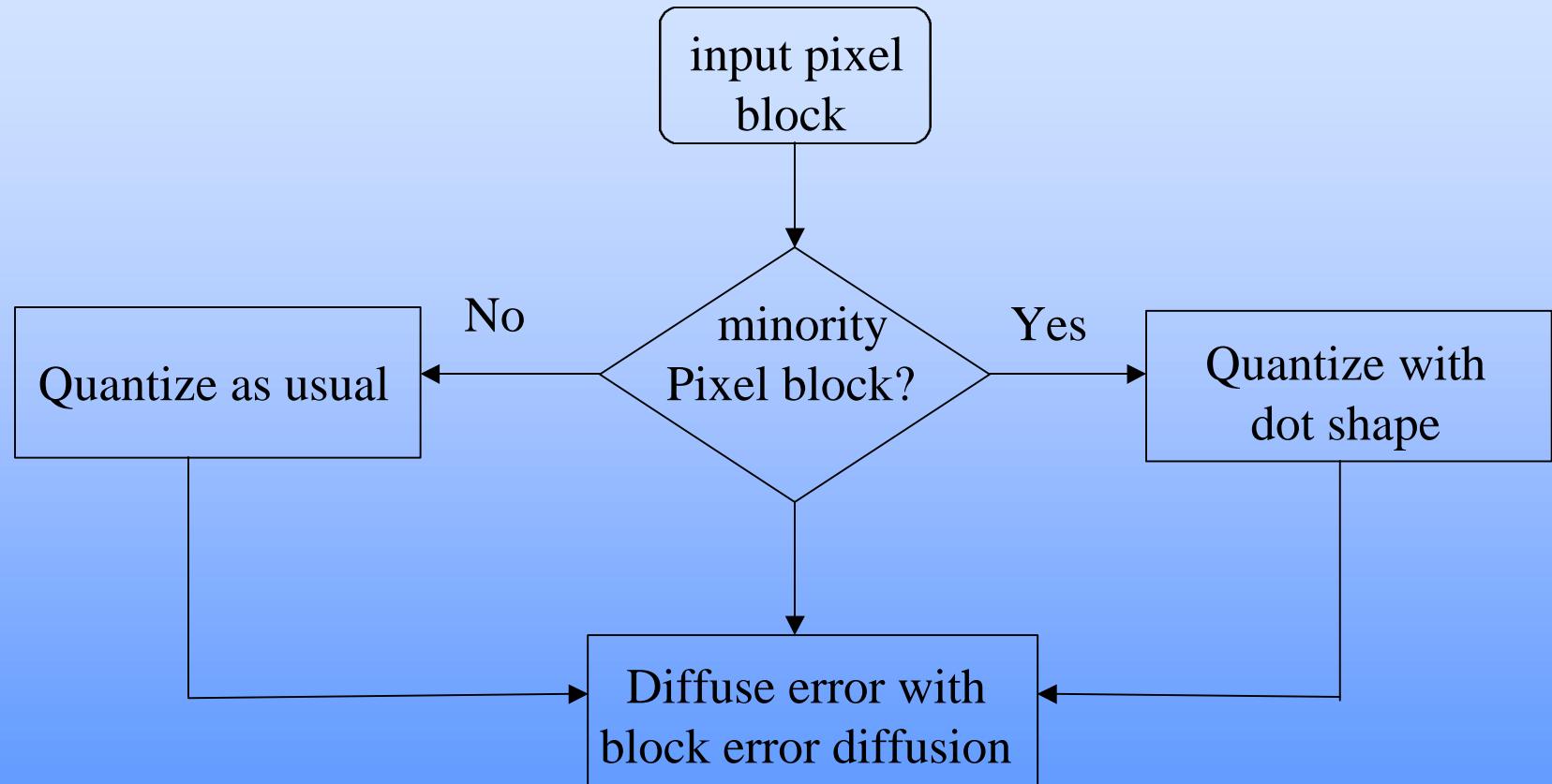
- **AM halftoning**
  - Vary dot size according to underlying graylevel
  - Clustered dot dither is a typical example (laserjet printers)
- **FM halftoning**
  - Vary dot frequency according to underlying graylevel
  - Error diffusion is typical example (inkjet printers)
- **AM-FM halftoning**
  - Vary dot size and frequency
  - Typical example is Levien's “green-noise” algorithm [Levien 1993]

# Designing Error Filter in Scalar Error Diffusion

- **Floyd-Steinberg error filter [Floyd and Steinberg, 1975]**
- **Optimize weighted error**
  - Assume error image is white noise [Kolpatzik and Bouman, 1992]
  - Use statistics of error image [ Wong and Allebach, 1997]
- **Adaptive methods**
  - Adapt error filter coefficients to minimize *local* weighted mean squared error [Wong, 1996]

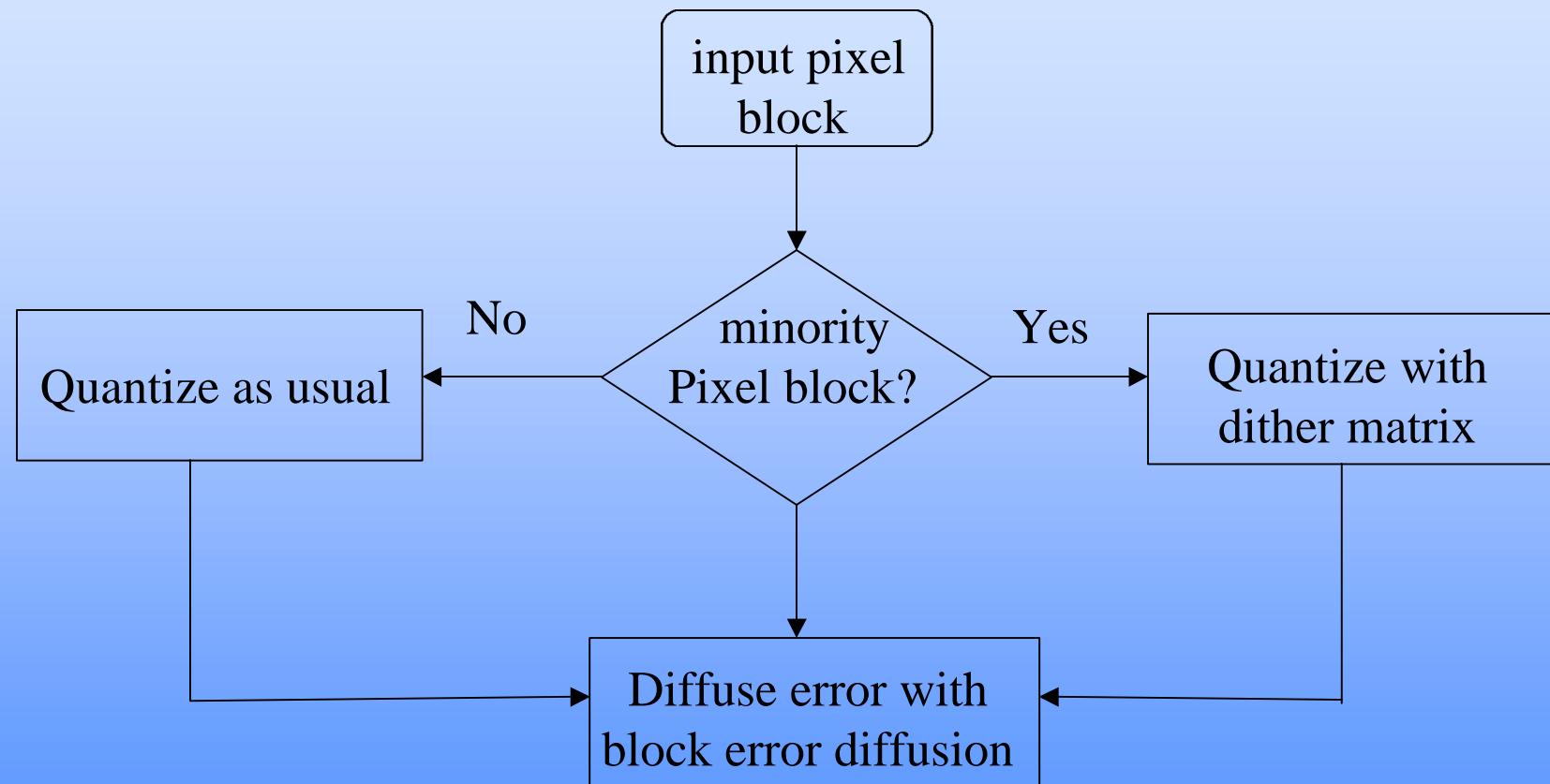
### Contribution #3: Block Error Diffusion

## FM Halftoning with Arbitrary Dot Shape



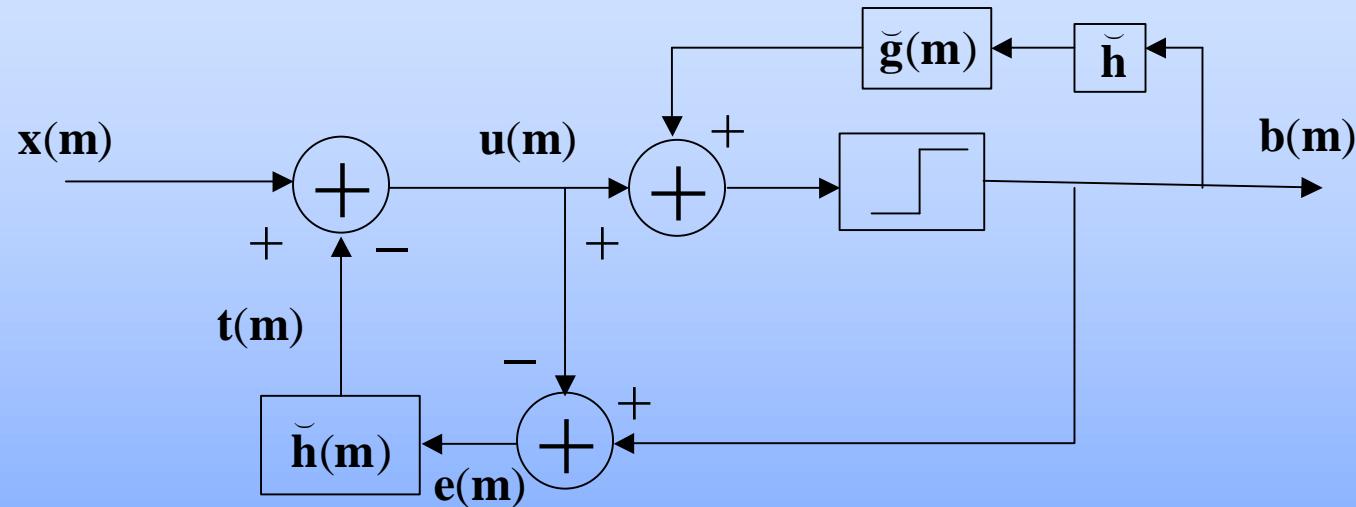
Contribution #3: Block Error Diffusion

## AM-FM Halftoning with User-controlled Dot Shape



Contribution #3: Block Error Diffusion

## AM-FM Halftoning with User-controlled Dot Size



Block green noise error diffusion

- Promotes pixel-block clustering into super-pixel blocks

Contribution #3: Block Error Diffusion

## AM-FM Halftoning Results



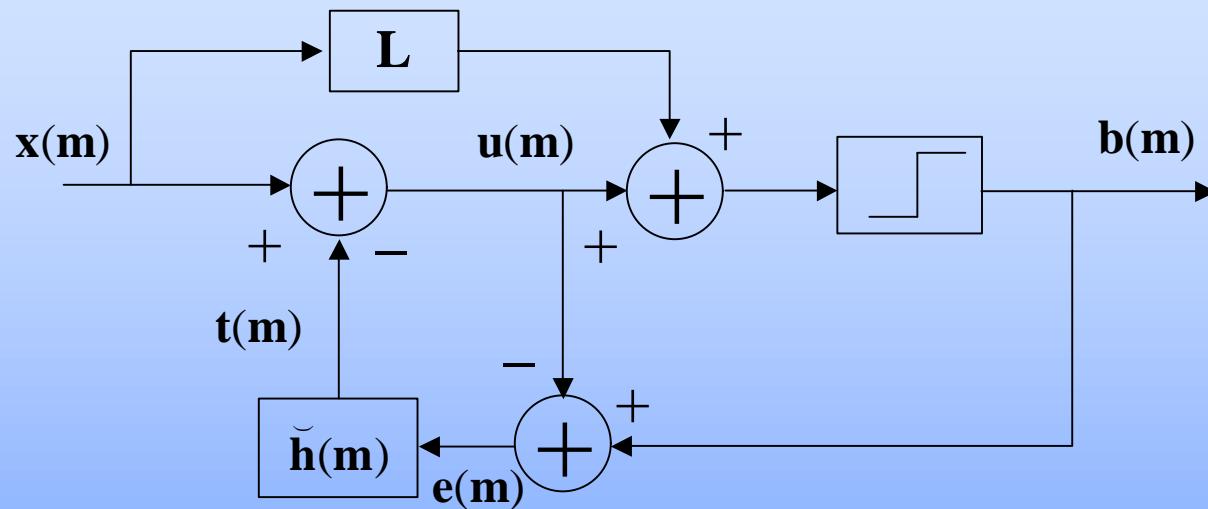
Clustered dot dither  
modulation



Output dependent  
feedback

Contribution #3: Block Error Diffusion

## Block FM Halftoning with Sharpness Control



Modified error diffusion

- The above block diagram is equivalent to prefiltering with

$$\check{\mathbf{G}}_s(\mathbf{z}) = [\check{\mathbf{I}} + \check{\mathbf{H}}(\mathbf{z})\{\check{\mathbf{I}} - \check{\mathbf{H}}(\mathbf{z})\}]\check{\mathbf{L}} + \check{\mathbf{I}}$$

Contribution #3: Block Error Diffusion

## Block FM Halftoning with Sharpness Control



$$\check{\mathbf{L}} = 0.2 \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\check{\mathbf{L}} = 0.6 \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Contribution #3: Block Error Diffusion

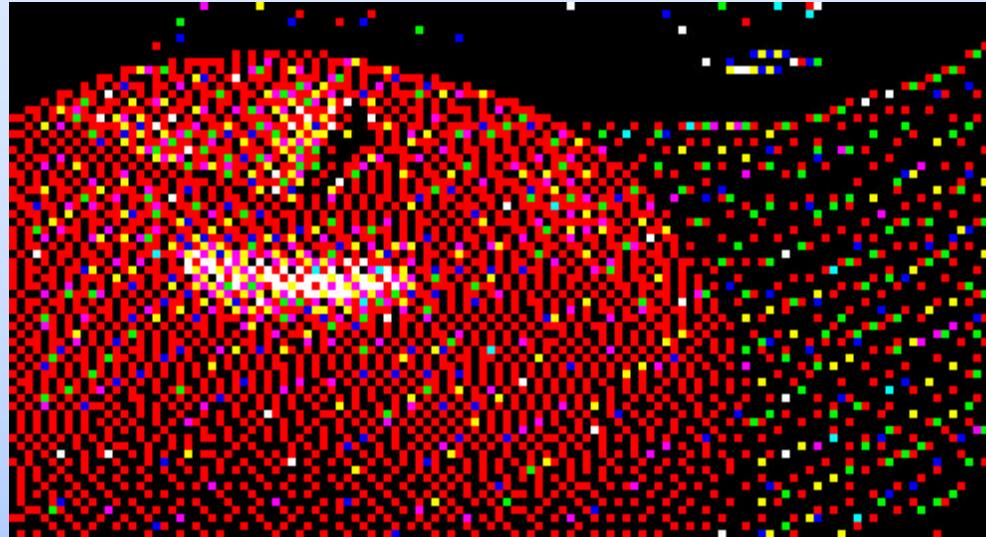
## Diffusion Matrix for Embedding

$$\mathbf{l} = (1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0)'$$

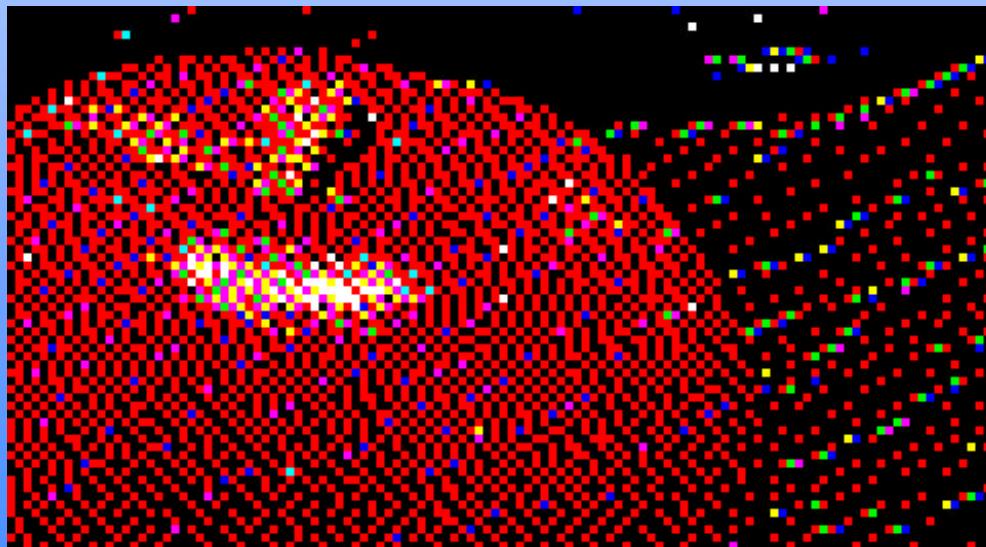
$$\mathbf{m} = \left( 0 \ 0 \ \frac{1}{3} \ 0 \ 0 \ 0 \ 0 \ 0 \ \frac{1}{3} \ 0 \ \frac{1}{3} \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \right)'$$

$$\mathbf{h} = \left( 0 \ \frac{1}{12} \ 0 \ \frac{1}{12} \ \frac{1}{12} \ \frac{1}{12} \ \frac{1}{12} \ \frac{1}{12} \ 0 \ \frac{1}{12} \ 0 \ \frac{1}{12} \ \frac{1}{12} \ \frac{1}{12} \ \frac{1}{12} \ \frac{1}{12} \right)'$$

$$\check{\mathbf{D}} = (\mathbf{l} \ \mathbf{h} \ \mathbf{m} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h} \ \mathbf{m} \ \mathbf{h} \ \mathbf{m} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h} \ \mathbf{h})'$$



Floyd-Steinberg

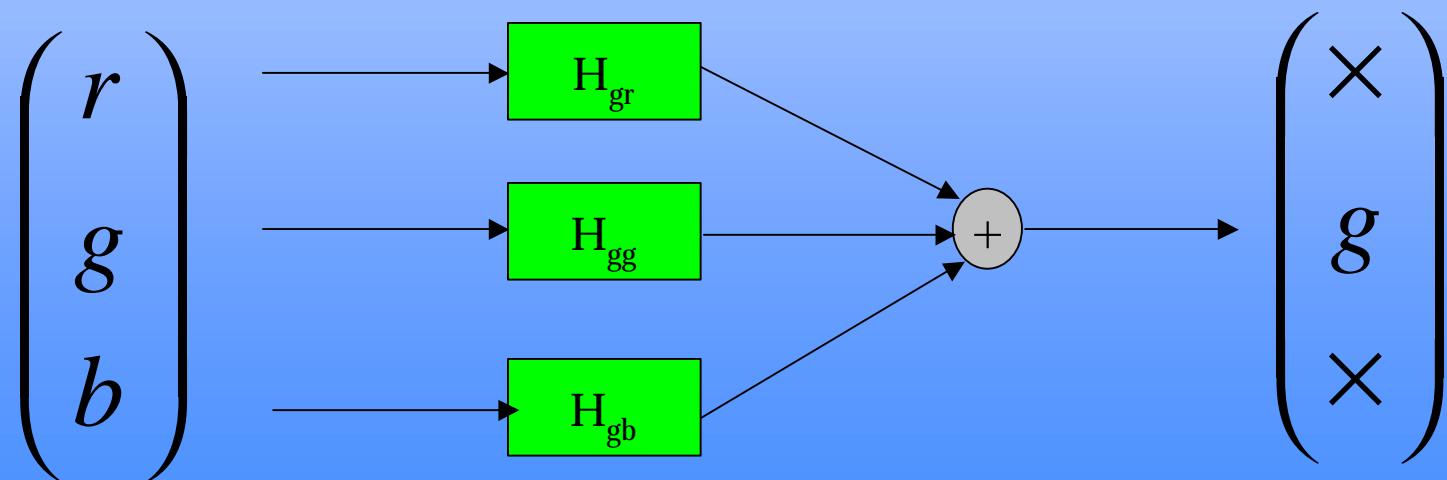


Optimum Filter

Contribution #4:

## Implementation of Vector Color Error Diffusion

$$\check{\mathbf{H}}(\mathbf{z}) = \begin{pmatrix} H_{rr}(\mathbf{z}) & H_{rg}(\mathbf{z}) & H_{rb}(\mathbf{z}) \\ H_{gr}(\mathbf{z}) & H_{gg}(\mathbf{z}) & H_{gb}(\mathbf{z}) \\ H_{br}(\mathbf{z}) & H_{bg}(\mathbf{z}) & H_{bb}(\mathbf{z}) \end{pmatrix}$$



Contribution #4:

## Implementation of Block Error Diffusion

