Technion – IIT
Dept. of Electrical Engineering
Signal and Image Processing Lab

Show-Through Cancellation in Scanned Images

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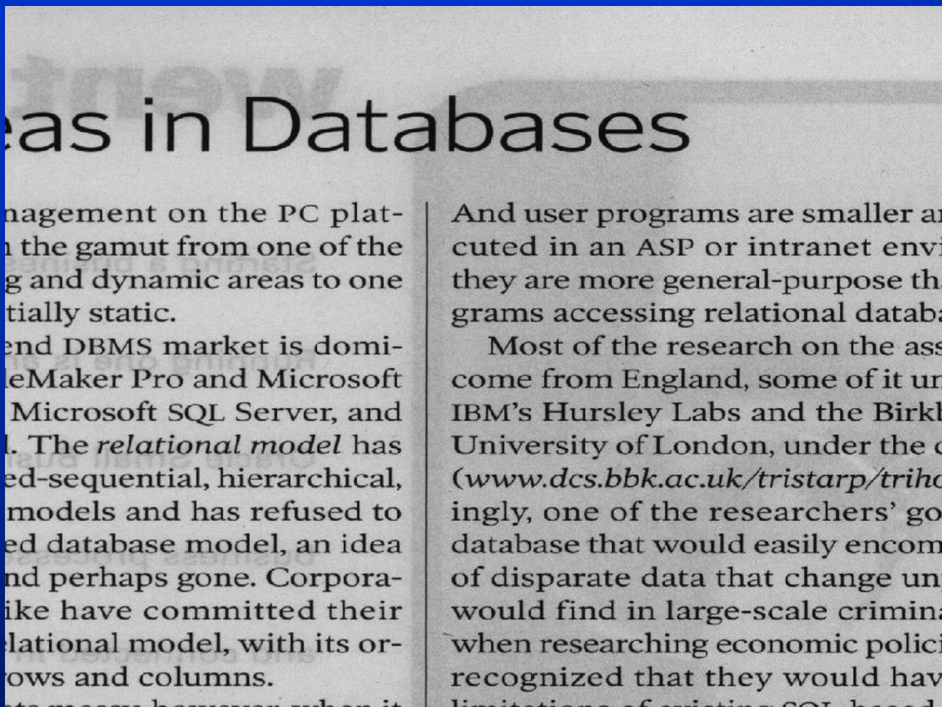
M.Sc. Research under the supervision

of Prof. David Malah

Show-Through in Scanned Images



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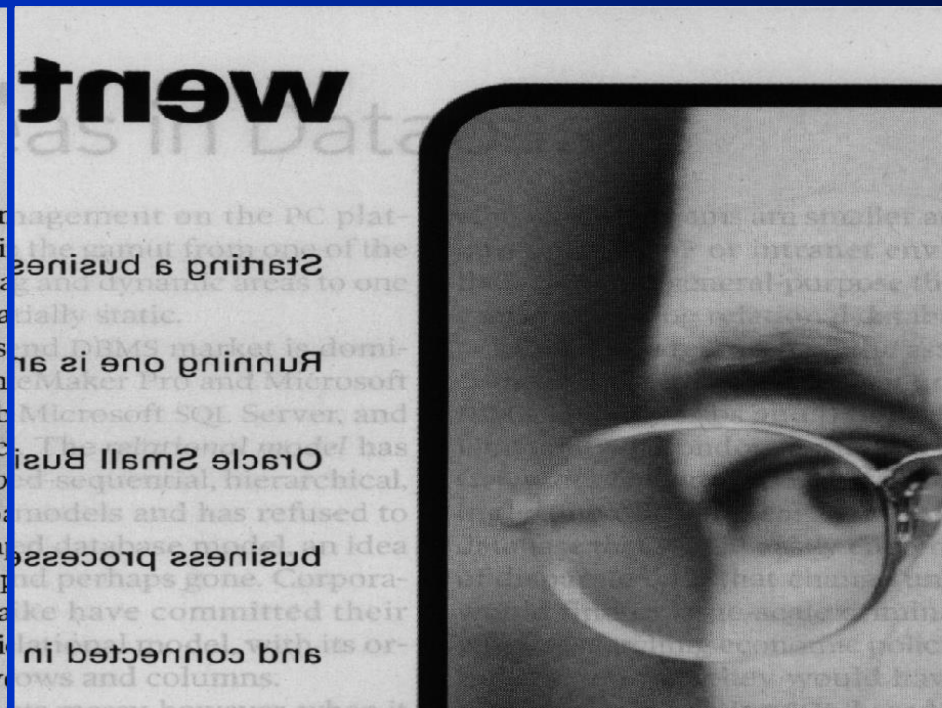


Goal : Remove cross-talk from images without distortion.

Talk Outline

- Previous work
- Physical model
- Decorrelation algorithm
  - Basic algorithm
  - Automatic background estimation
  - Local background normalization
  - Adaptive post-processing
  - Cascaded filter structure
- BSS algorithm
  - TV Regularization
  - Fidelity/Regularization Tradeoff
  - ICM
- Conclusions and Future work

Previous Work

Show-Through Removal in Scanned Images

- Sharma (`01)

Image Mixtures (Separating Reflections)

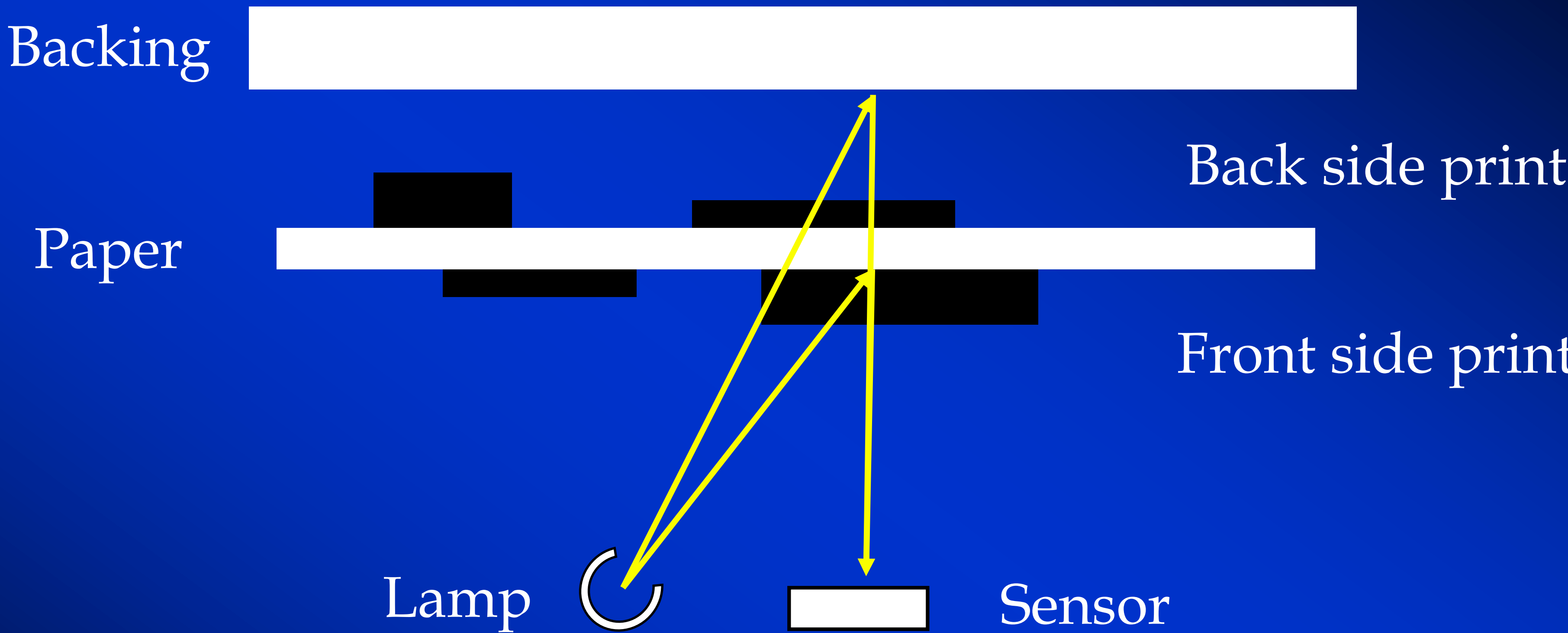
- Farid & Adelson (`99) – linear mixtures, ICA
- Schechner, Kiryati & Basri (`00) – convolutive mixtures, mutual information
- Bronstein^2, Zibulevsky & Zeevi (`03) – sparse ICA
- Sarel & Irani (`04) – spatially varying linear mixtures
- Levin, Zomet & Weiss (`04) – single image
- Tonazzini *et al* (`01-`05) – linear pointwise and convolutive image mixtures, MRFs

Related Problems

- Multi-channel systems : Weinstein, Feder & Oppenheim (`93), Thi & Jutten (`95) – BSS of convolutive mixtures
- Deconvolution : Bronstein^2, Zibulevsky & Zeevi (`05) - sparsity, Chan & Wong (`98) , Kaftory, Sochen & Zeevi (`05)– TV, many others…

Physical Model

Physical Model - 1



$$R_f^s = T_f^2(R_p + T_p^2 R_{bk} T_b^2)$$

$$R_f = T_f^2(R_p + T_p^2 R_{bk})$$

R - Reflectance

T - Transmittance

Physical Model - 2

Definitions:

Reflectance of white paper: $$R_p^w = R_p + T_p^2 R_{bk}$$

Normalized Optical Density

$$D = -\ln \frac{R}{R_p^w}$$

Normalized Optical Absorptance

$$A = 1 - \frac{R}{R_p^w}$$

Linearized Creation Model:

$$D_f^s(x,y) \simeq D_f(x,y) + \frac{T_p^2 R_{bk}}{R_p + T_p^2 R_{bk}} h(x,y) * A_b(x,y)$$

Show-Through Removal by Decorrelation

Basic Cleaning Algorithm
(Sharma 2001)

- R_p^w - Manual estimation.
- Front-side reflectance → Density.
- Back-side reflectance → Absorptance.
- For each pixel (progressing in a spatial contiguous order):
  - Compute show-through corrected density:

$$D_f(m,n) = D_f^s(m,n) - \sum_{k=-N}^{N} \sum_{l=-N}^{N} w(k,l) A_b^s(m-k, n-l)$$

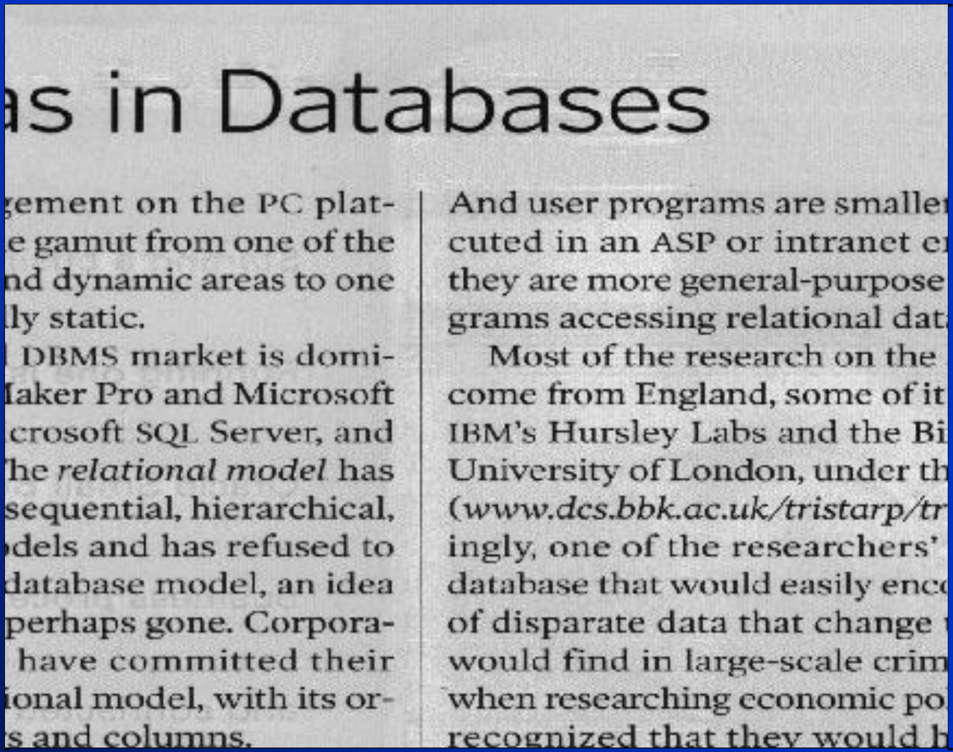
  - If back side has activity but not front side, update filter coefficients by LMS method:

$$w'(k,l) = w(k,l) + \mu D_f(m,n) A_b^s(m-k, n-l)$$

$$w(k,l) = w'(k,l)$$

  - Convert density to reflectance.

Results - Sharma



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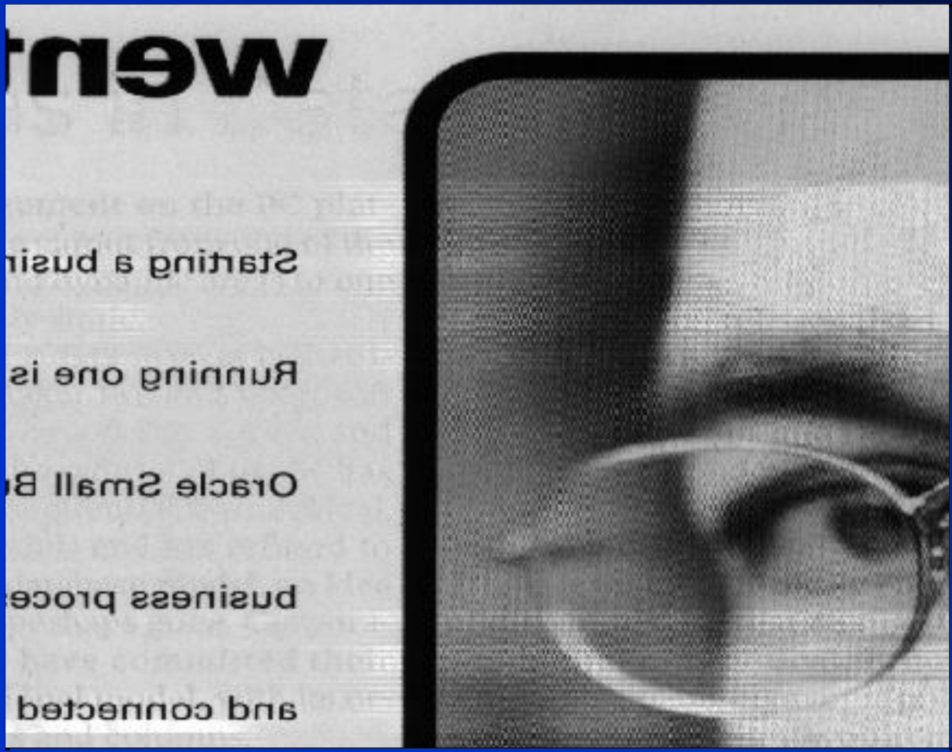
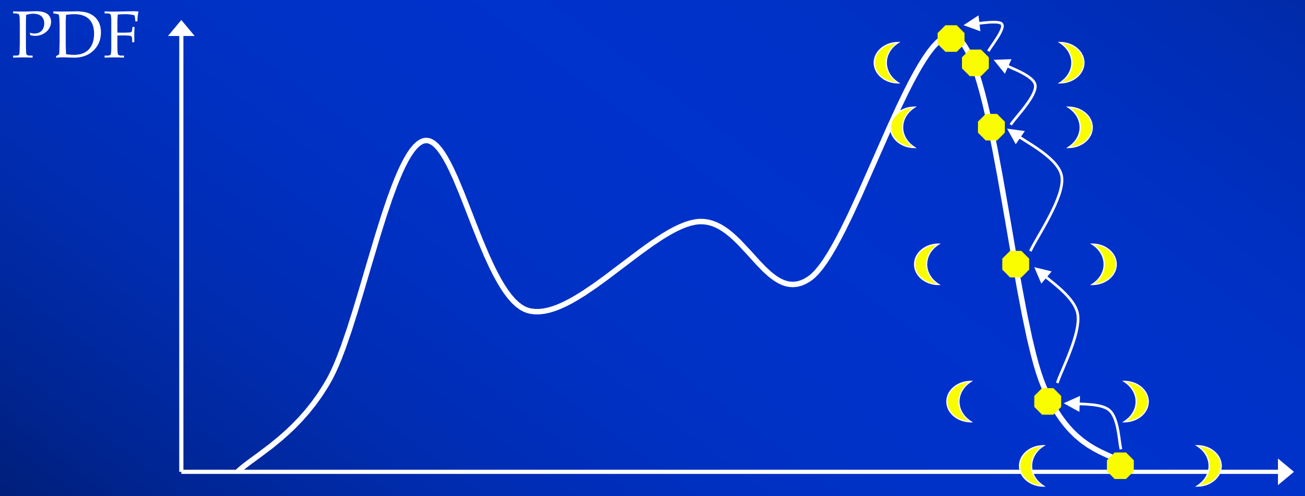


	Before	After
Corr	0.25	0.05
MI	0.1	0.02

Automatic Background Estimation

Mean-Shift algorithm (Fukunaga (`75), Cheng (`95), Meer (`02)) :

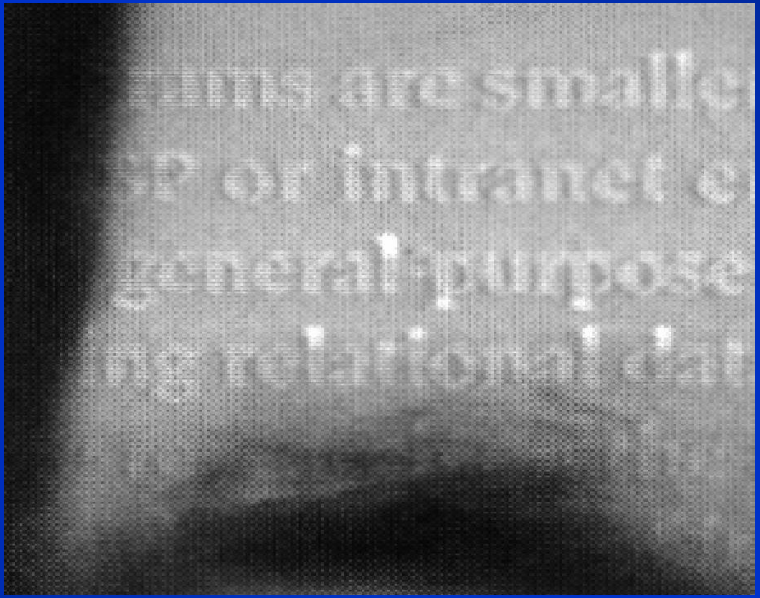
- Iterative steepest ascent algorithm
- Converges to local maximum



- Start point – brightest pixel
- Window size – proportional to signal STD

Local Background - 1

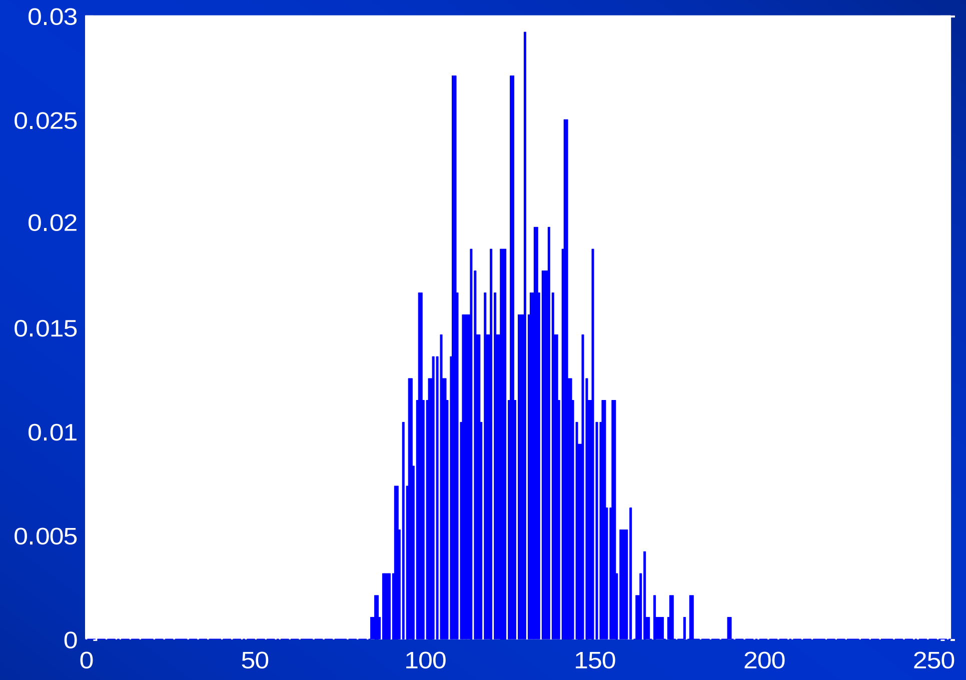
- Algorithm attempts to bring error to "zero", defined by R_p^w
- Problem:



- Solution : Local background is calculated by a mean shift process on histogram of local neighborhood

Local Background - 2

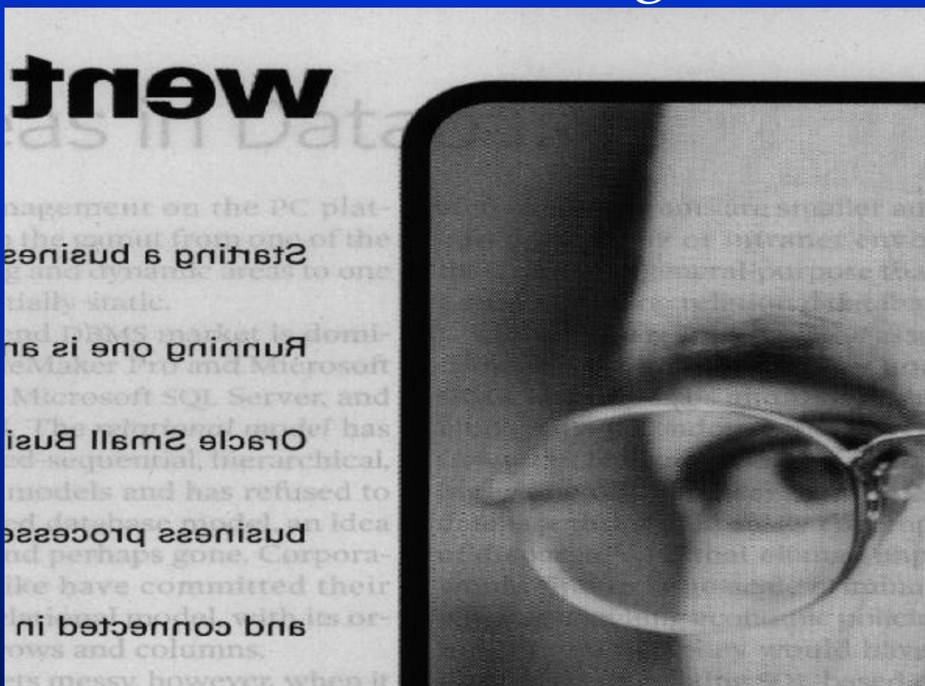
- Problem : Local histogram not a "good" approximation of PDF



- Solution : Adaptive mean-shift – variable window size
  - Increase window size until it covers enough pixels
- When reverse-side activity is high, Global value is used

Local Background - 3

Scanned Image



Background Image

- Global Background = 209

Decorrelation Systems

Construction System

$$\begin{cases} X_1 = S_1 + H_1 S_2 \\ X_2 = S_2 \end{cases}$$

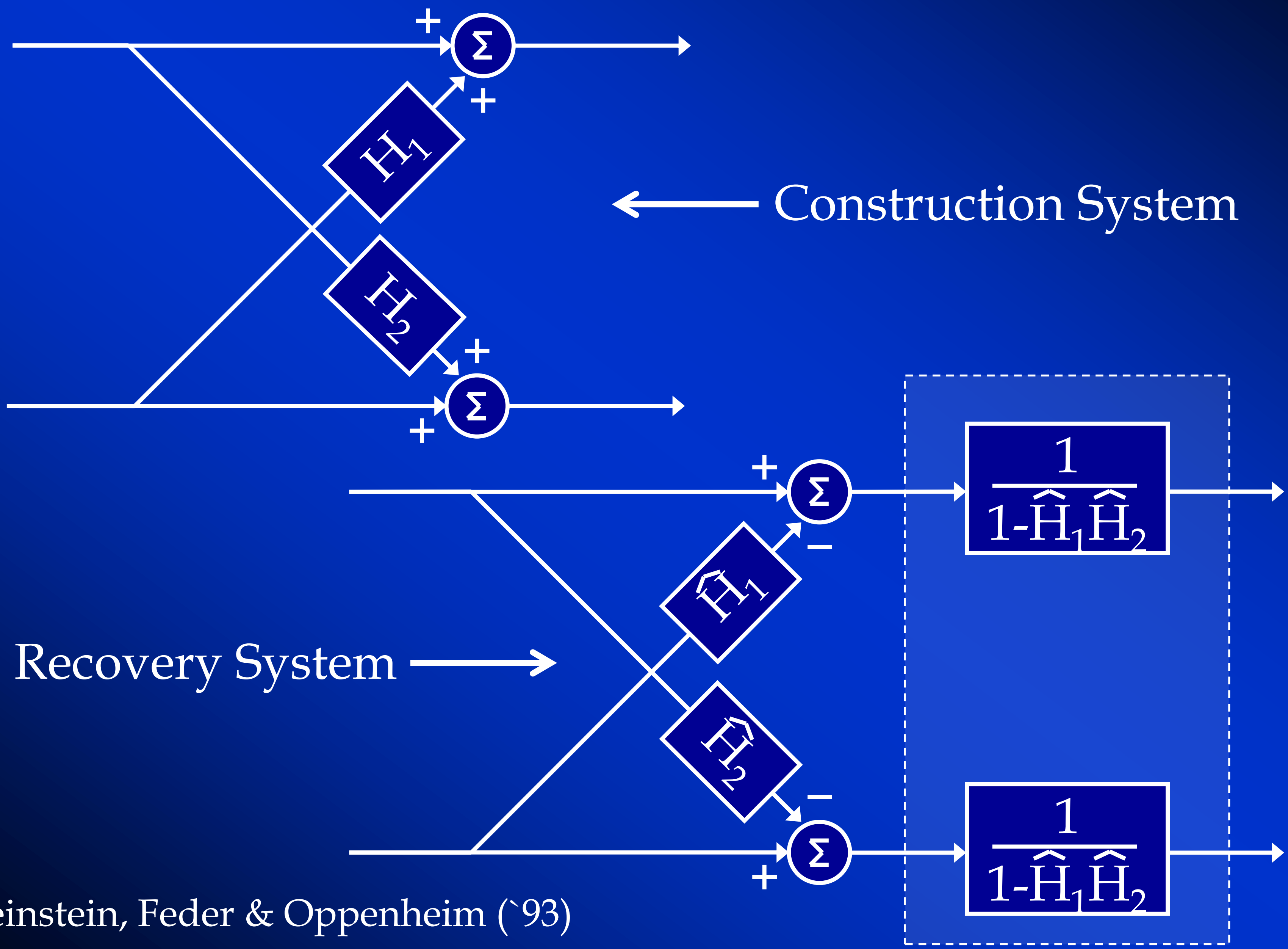
Recovery System

$$S_1 = X_2 - H_2 X_1$$

$$\begin{cases} X_1 = S_1 + H_1 S_2 \\ X_2 = S_2 + H_2 S_1 \end{cases}$$

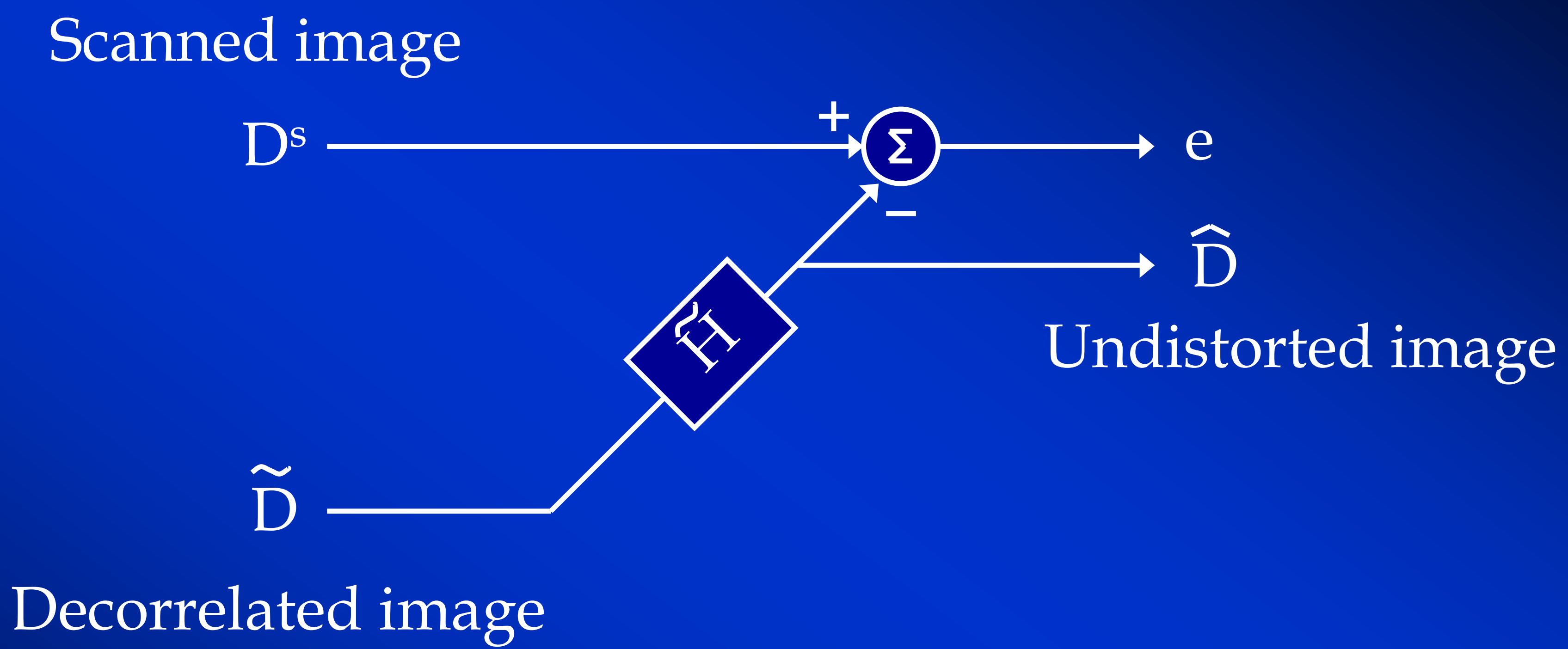
$$\begin{cases} S_1 = \dfrac{X_1 - H_1 X_2}{(1 - H_1 H_2)} \\ S_2 = \dfrac{X_2 - H_2 X_1}{(1 - H_1 H_2)} \end{cases}$$

Decorrelation Systems



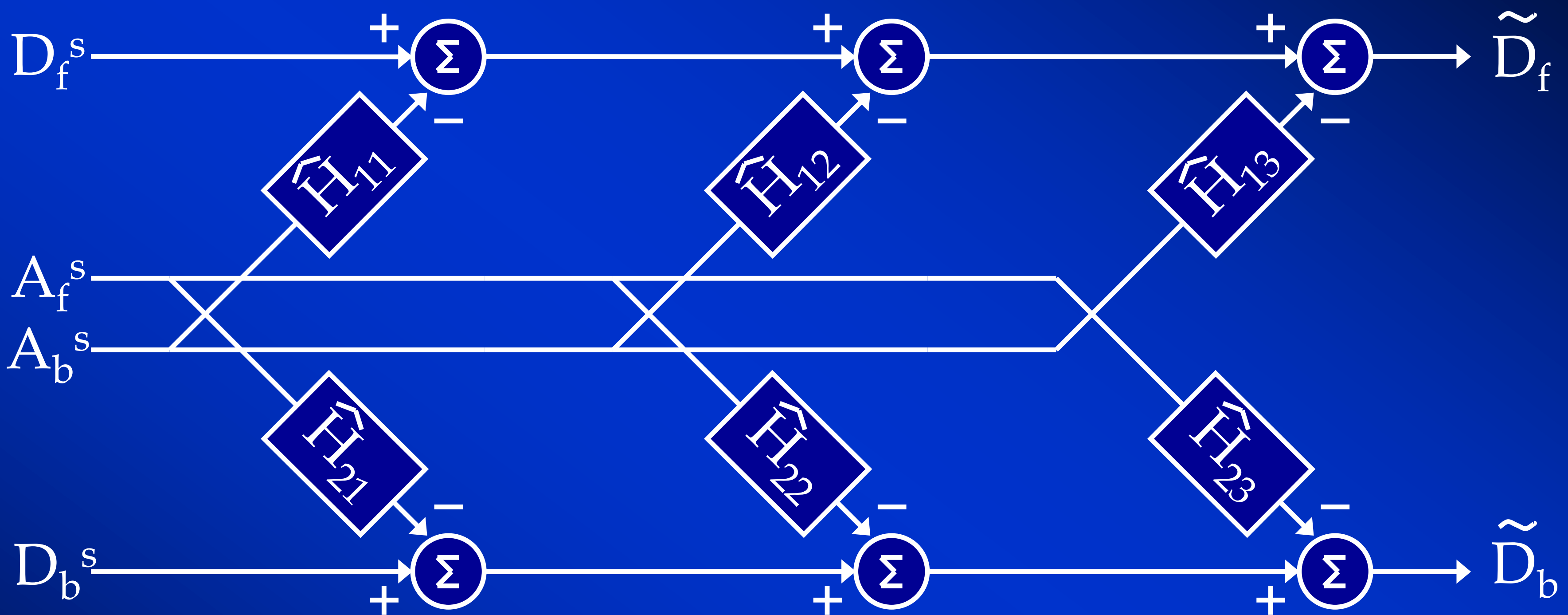
Weinstein, Feder & Oppenheim (`93)

Adaptive Post-Processing



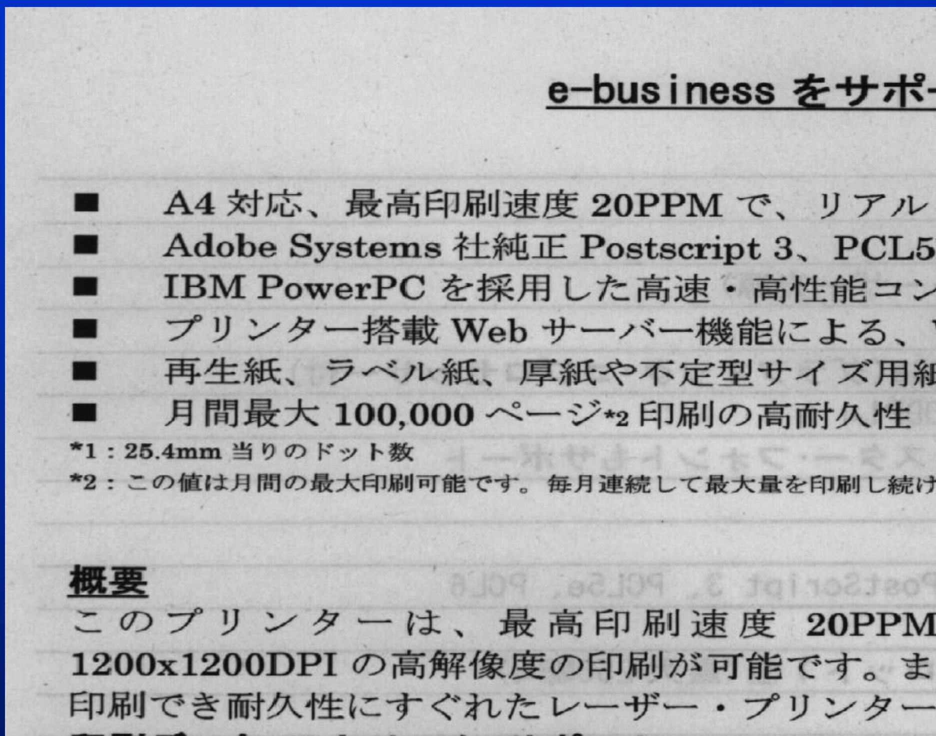
- Removes inherent distortion
- Removes some artifacts
- Degrades decorrelation somewhat

Cascaded Filter Structure



- Filter support increases with each stage
  - Typical values - 5x5, 9x9 & 15x15 pixels

Experimental Results

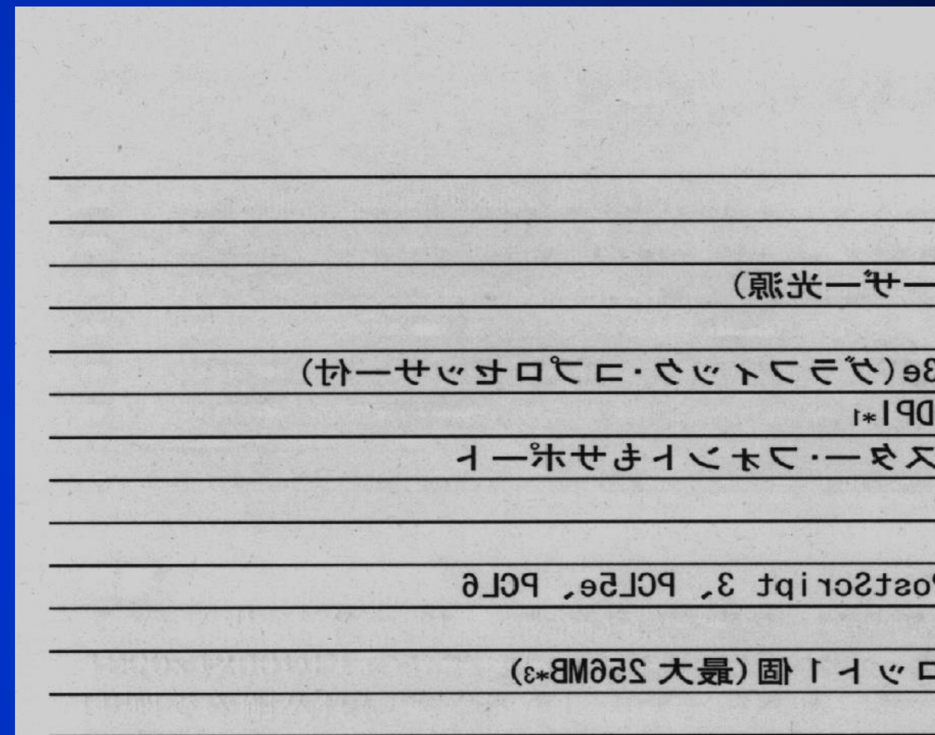


e-business をサポー

■ A4 対応、最高印刷速度 20PPM で、リアル
■ Adobe Systems 社純正 Postscript 3、PCL5
■ IBM PowerPC を採用した高速・高性能コン
■ プリンター搭載 Web サーバー機能による、W
■ 再生紙、ラベル紙、厚紙や不定型サイズ用紙
■ 月間最大 100,000 ページ*2 印刷の高耐久性

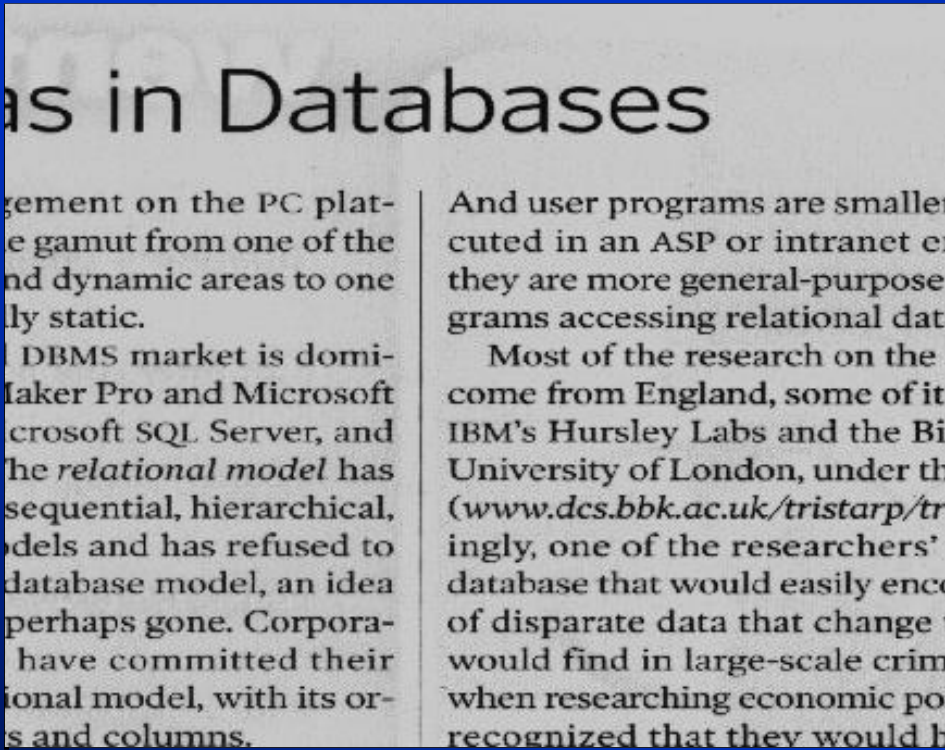
*1：25.4mm 当りのドット数
*2：この値は月間の最大印刷可能です。毎月連続して最大量を印刷し続け

概要
このプリンターは、最高印刷速度 20PPM
1200x1200DPI の高解像度の印刷が可能です。ま
印刷でき耐久性にすぐれたレーザー・プリンター



	Before	After
Corr	0.17	0.015
MI	0.09	0.025

Experimental Results



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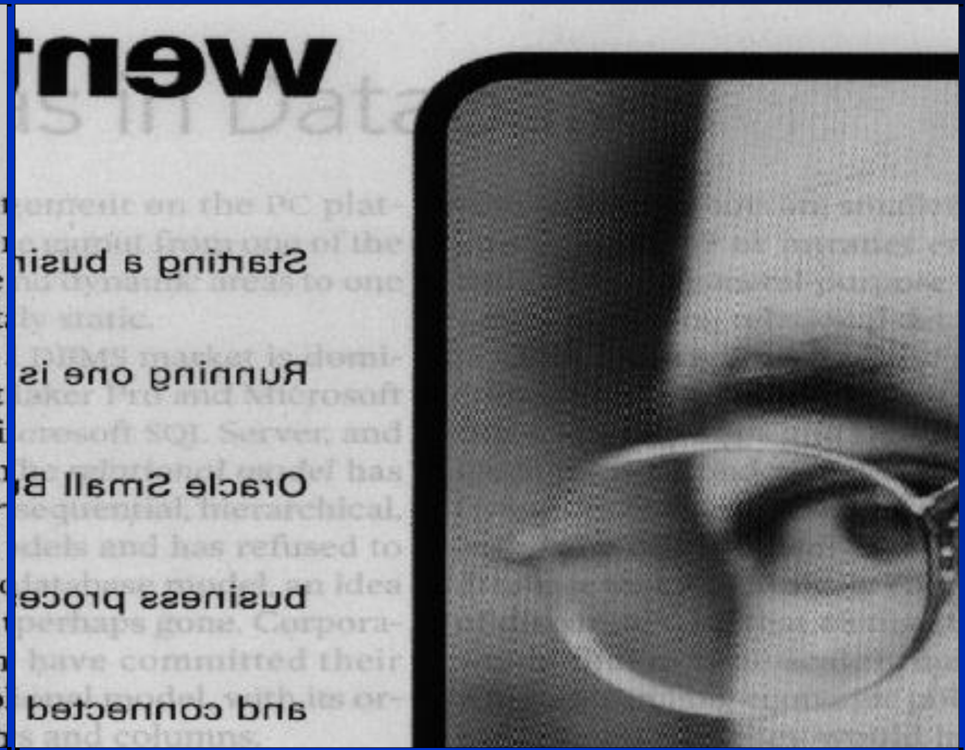


	Before	Sharma	After
Corr	0.25	0.05	0.03
MI	0.1	0.02	0.01

Decorrelation Algorithm Summary

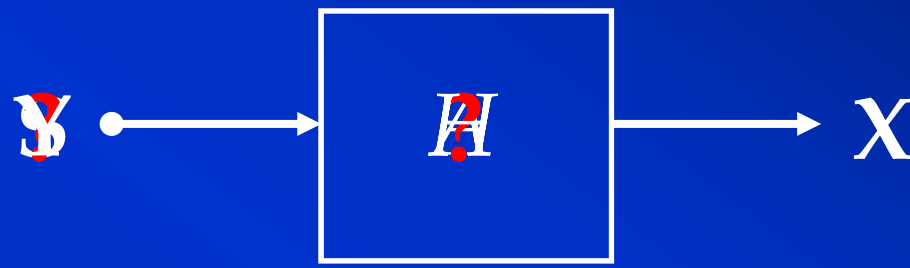
- Improved algorithm includes:
  - Local background normalization
  - Adaptive post-processing stage
  - Cascaded filter structure

- Algorithm achieves improved results.

- Algorithm handles scans of complex documents containing text and images.

Show-Through Removal
by
Blind Source Separation
(BSS)

Show-Through as a BSS Problem



- Goal – estimate images **Y** and mixing parameters *H*
- Method: Minimization of a Cost Function

$$J = \left\| H(\mathbf{Y}) - \mathbf{X} \right\|_2^2$$

Image Separation as a Regularization Problem

$$J = \left\| H(\mathbf{Y}) - \mathbf{X} \right\|_2^2 + \lambda_1 \operatorname{Re} g(Y_1) + \lambda_2 \operatorname{Re} g(Y_2)$$

- Assumption: Images Y1 and Y2 are independent
- Regularization Functions:
  - Smoothness
  - Markov Random Fields
  - Total Variation

Simple
Oversmoothing

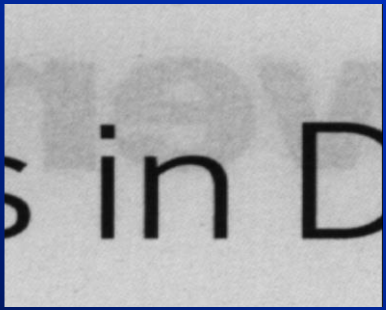
Edge Preserving
Many Parameters
Non Convex

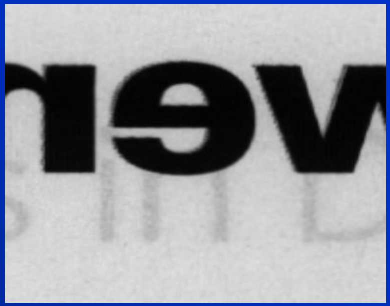
Edge Preserving
Convex

Fidelity/Regularization Tradeoff

$$J = \left\| H(\mathbf{Y}) - \mathbf{X} \right\|_2^2 + \lambda_1 TV(Y_1) + \lambda_2 TV(Y_2)$$

- Tradeoff ratio λ determines strength of edges to be preserved.
- Strong *et al* (`97) suggest location dependent λ inversely proportional to gradient strength, in the context of image restoration.
  - λ is set separately for vertical and horizontal edges.
- Problem: Show-Through interference contains edges itself.





Fidelity/Regularization Tradeoff

$$J = \left\| H(\mathbf{Y}) - \mathbf{X} \right\|_2^2 + \lambda_1 TV(Y_1) + \lambda_2 TV(Y_2)$$

- Solution: Weighting is set using both images.
- Strong edge in one image and weak edge at the same location in the other image => Probable Show Through scenario
  - Set **high** λ at show through edge
    - proportional to true (reverse side) edge strength
  - Set **low** λ at true edge
    - inversely proportional to edge strength

Example lambda maps

Scanned Images

Horizontal gradient
λ maps

Alternating Minimization

$$J = \left\| H(\mathbf{Y}) - \mathbf{X} \right\|_2^2 + \lambda_1 TV(Y_1) + \lambda_2 TV(Y_2)$$

- Simultaneous minimization is very difficult:
  - Non-linear in joint space $\{H, \mathbf{Y}\}$
  - Non-convex in joint space $\{H, \mathbf{Y}\}$
  - Large number of variables
- Reduction method:

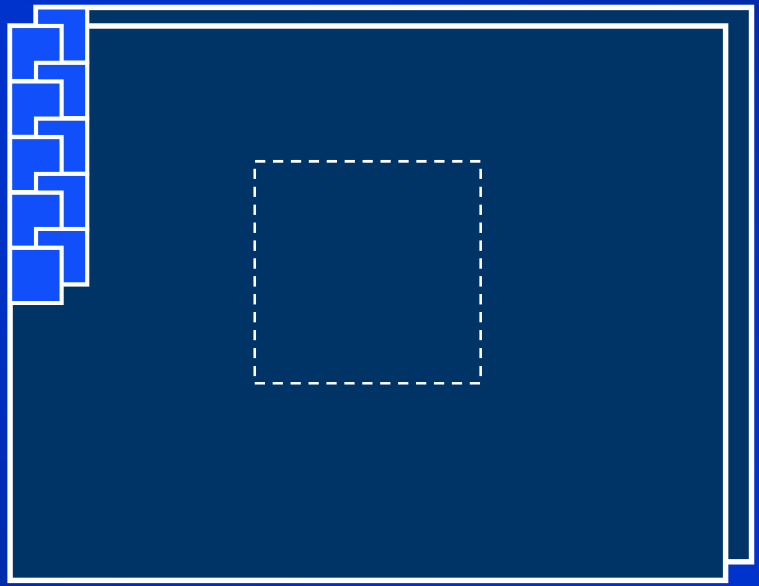
  Alternating Minimization in $\mathbf{Y}$ and H

  - Linear optimization problems
  - Convex cost functional

Iterated Conditional Modes (ICM)

Besag (1986)

- **Y** optimization is done on a very large number of dependent variables



- J is minimized one pixel location at a time.
- Each minimization is done only on partial sum of elements of J.
- Pixel values updated in place.
- Algorithm typically converges after 3-5 passes.
- To avoid directional preference we alternate pass direction.

Mixing Parameter Estimation

$$J = \left\| H(\mathbf{Y}) - \mathbf{X} \right\|_2^2$$

- Assumption: *H* is the same throughout the image

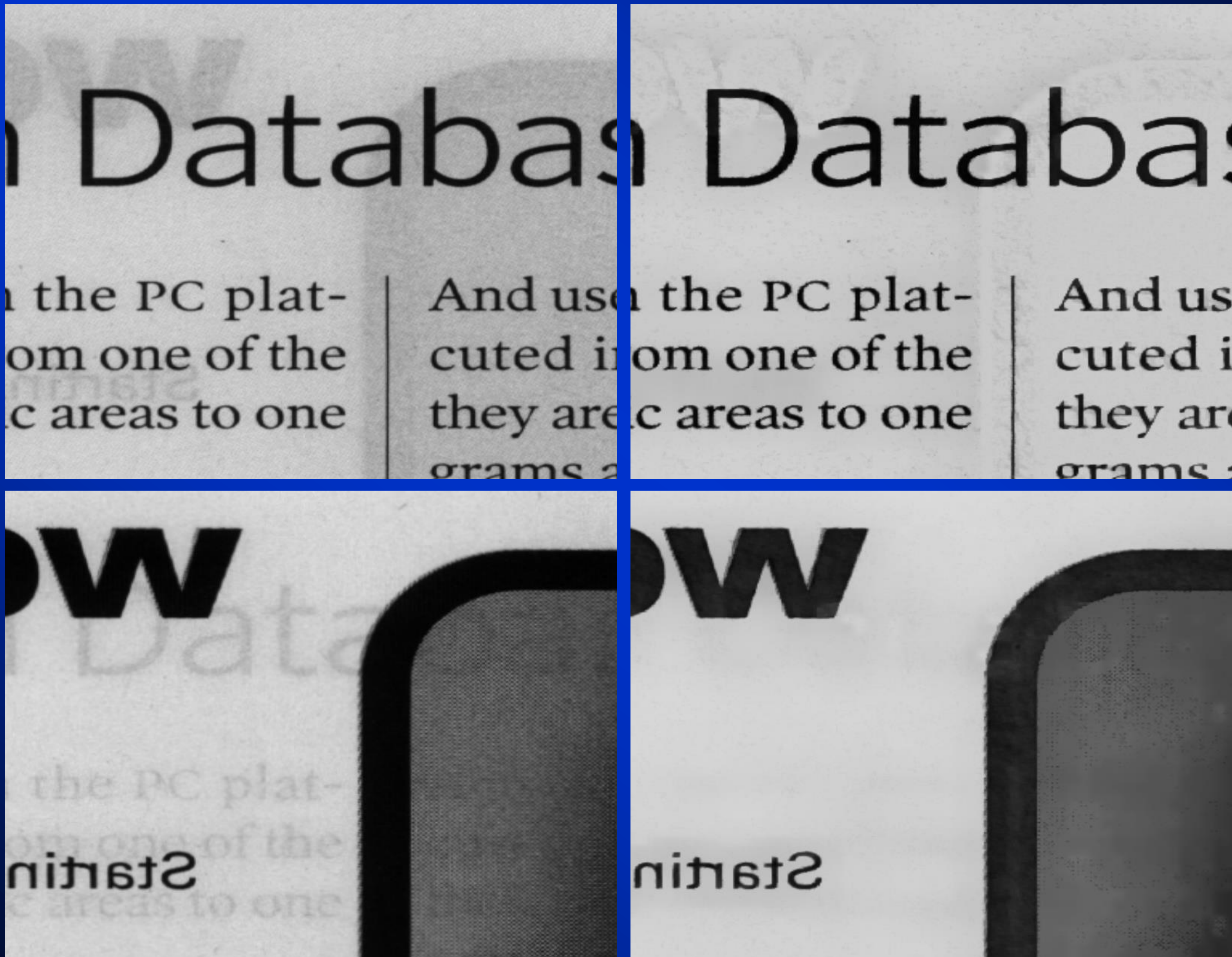
$$H = \begin{pmatrix} 1 & h_{12} * f(\cdot) \\ h_{21} * f(\cdot) & 1 \end{pmatrix}$$

- Least Squares problem
- Many pixels do not contribute to the solution
- Activity Masks – only pixels with single sided activity

Minimization Algorithm

- Estimate Background
- Initialization : Y=X, $H = \begin{pmatrix} 1 & \varepsilon \\ \varepsilon & 1 \end{pmatrix}$
- Alternating Optimization:
  - Y Optimization:
    - Compute λ maps
    - ICM Iterations
      - Top-Bottom scan
      - Bottom-Top scan
  - *H* Optimization:
    - Compute activity masks
    - Least-Squares minimization
  - Normalize PSFs and images
- Repeat for larger filter support

Experimental Results



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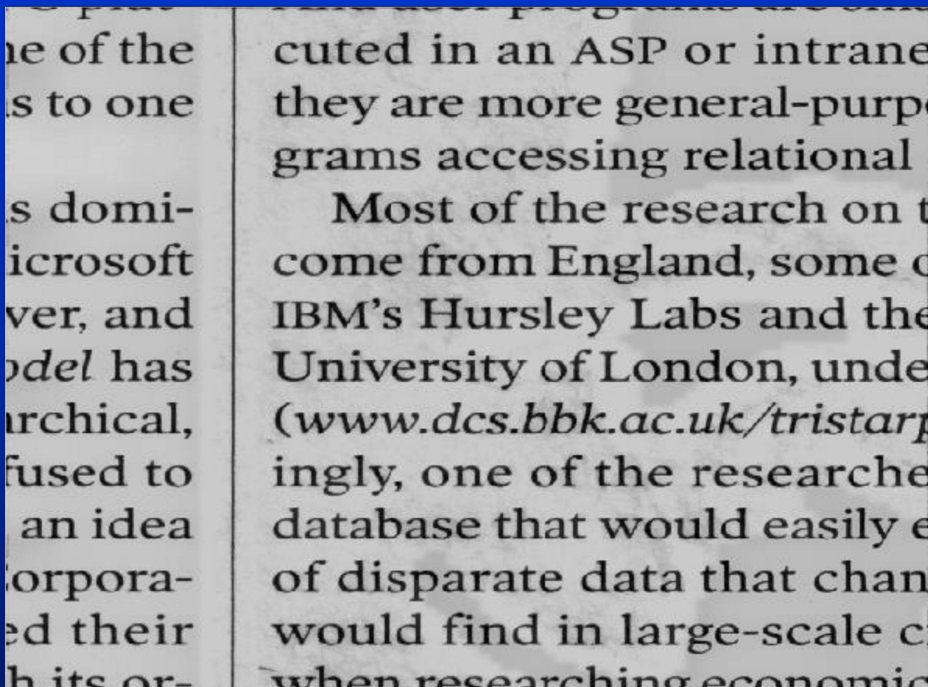

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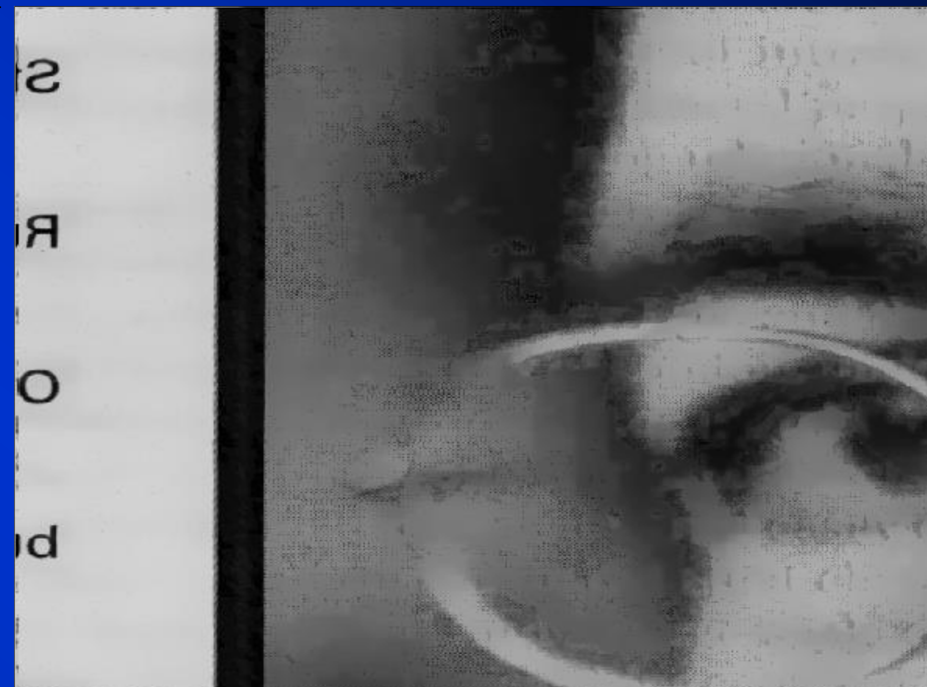

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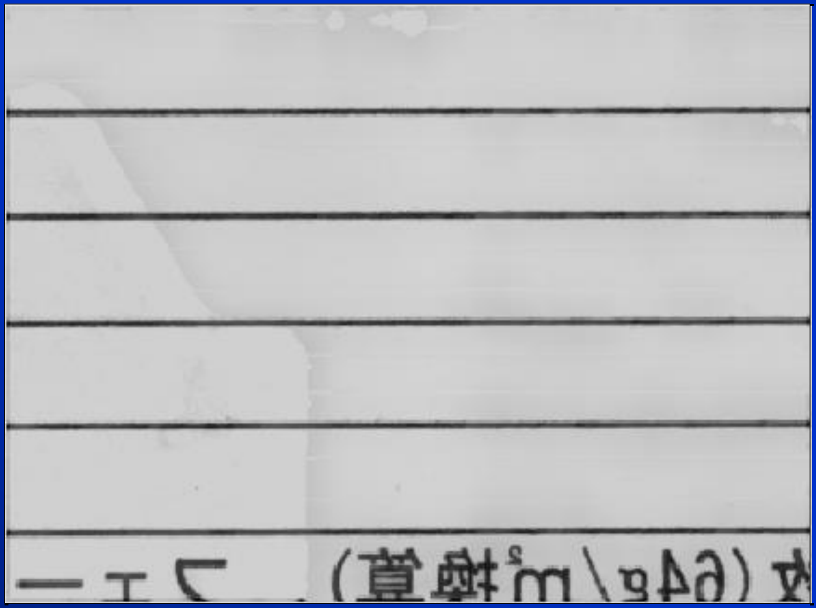

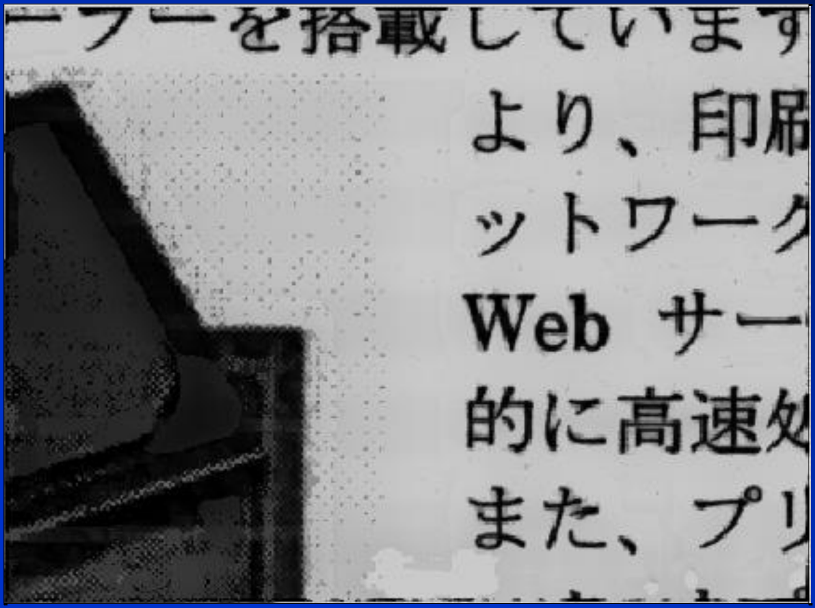

Conclusions and Future Work

Conclusions

- Show-Through as a non-linear convolutive mixture of images.
- Two algorithms were proposed:
  - Decorrelation – good results at low computation cost
  - BSS – high computation, way of the future

Future Work

- Technical Improvements
  - Better numerical approximations
  - Better optimization schemes
- Theoretical Extensions
  - Better image models
  - Color Images

Thank You

Algorithm Complexity

Decorrelation Algorithm:

- Per filtering stage
  - Per Pixel
    - Compute cleaned pixel value
    - Update PSF values

BSS Algorithm:

- Per ICM iteration
  - Per Pixel location
    - Minimization of partial sum of J
      - Number of elements in partial sum depends on PSF support
      - Optimization by Line-Search
        - Gradient estimation (2 function calculations)
        - Line-Search iterations (typically 4-6 steps)