Other Tone Adjustment Methods

- Interactive Local Adjustment of Tonal Values
  - Lischinski *et al.*
  - SIGGRAPH 2006

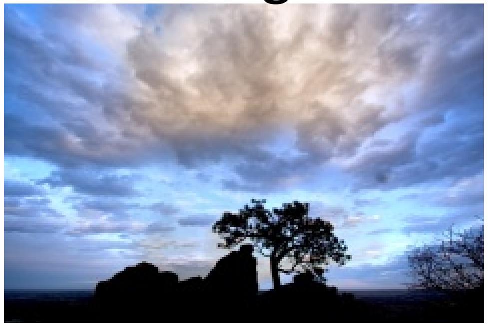
Interactive Local Adjustment of Tonal Values

Three Renditions of One Digital Negative

warm sky

cool sky

black foreground

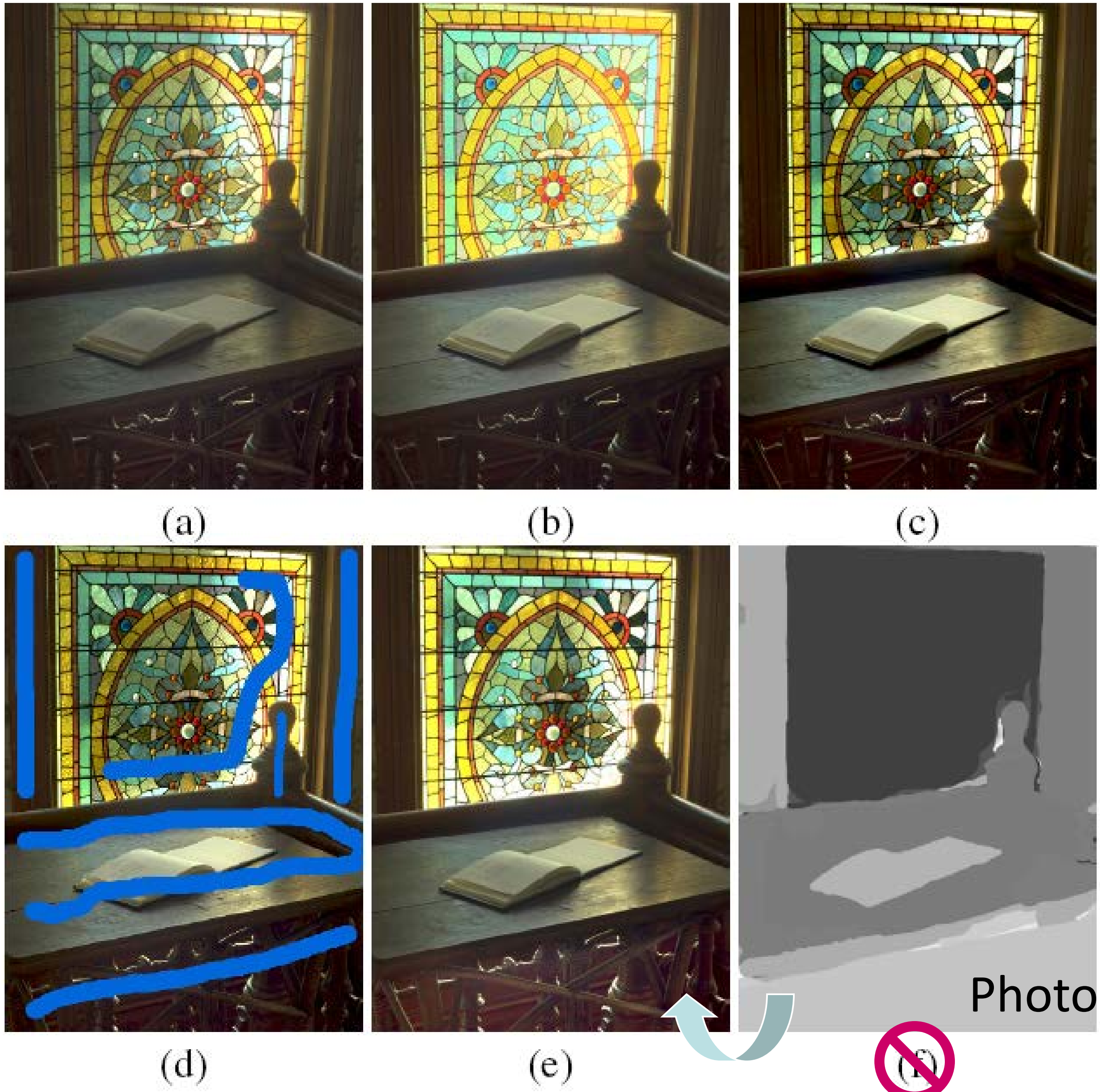


scribble-based user interface

available adjustments:
exposure, contrast, saturation, color temperature

other applications:
LDR enhancement, spatial varying white balance,
spatial varying blur

gradient domain photographic interactive



Photoshop

Demo Video

- http://www.cs.huji.ac.il/~danix/itm/itm-divx.avi

Strokes and Brushes

- Basic brush
  - Assigning a weight of 1.0
- Luminance brush $w(\ell) = \exp(-|\ell - \mu|^2/\sigma^2).$

  mean lightness value of pixels under the stroke

  - To apply a constraint to pixels whose luminance is similar to those covered by the brush stroke
- Lumachrome brush
  - CIE *L*a*b** color space
- Over-exposure brush
  - Select all over-exposed pixels inside a given region

Lumachrome Brush

- For fragmented regions with similar colors

Constraint Propagation

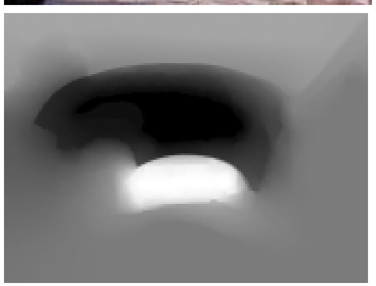
- Spatial varying exposure function

$$f = \arg\min_{f} \left\{ \sum_{\mathbf{x}} w(\mathbf{x}) \left(f(\mathbf{x}) - g(\mathbf{x}) \right)^2 + \lambda \sum_{\mathbf{x}} h(\nabla f, \nabla L) \right\}$$

related pixels

data term

smoothness term



exposure adjustment map

$g(\mathbf{x})$ target exposure values

$$h(\nabla f, \nabla L) = \frac{|f_x|^2}{|L_x|^\alpha + \varepsilon} + \frac{|f_y|^2}{|L_y|^\alpha + \varepsilon}$$

log-luminance

$$\lambda = 0.2,\ \alpha = 1,\ \text{and}\ \varepsilon = 0.0001$$

Minimization

$$f = \arg\min_{f} \left\{ \sum_{\mathbf{x}} w(\mathbf{x}) \, (f(\mathbf{x}) - g(\mathbf{x}))^2 + \lambda \sum_{\mathbf{x}} h(\nabla f, \nabla L) \right\} \qquad h(\nabla f, \nabla L) = \frac{|f_x|^2}{|L_x|^\alpha + \varepsilon} + \frac{|f_y|^2}{|L_y|^\alpha + \varepsilon}$$

Euler-Lagrange equation $\frac{\partial E}{\partial f} - \frac{d}{dx}\frac{\partial E}{\partial f_x} - \frac{d}{dy}\frac{\partial E}{\partial f_y} = 0$

$$\frac{\partial E}{\partial f} = 2 \sum_{\mathbf{x}} w(\mathbf{x}) \Big(f(\mathbf{x}) - g(\mathbf{x}) \Big)$$

$$\frac{d}{dx}\frac{\partial E}{\partial f_x} = 2\lambda \sum_{\mathbf{x}} \frac{f_{xx}}{|L_x|^\alpha + \epsilon}$$

$$\mathbf{x} = (x, y)$$

$$\frac{d}{dy}\frac{\partial E}{\partial f_y} = 2\lambda \sum_{\mathbf{x}} \frac{f_{yy}}{|L_y|^\alpha + \epsilon}$$

$$\boxed{\mathbf{A} f = b}$$

apply finite difference

$$f_{xx} = f(x+1,y) - f(x,y) - (f(x,y) - f(x-1,y))$$
$$= f(x+1,y) + f(x-1,y) - 2f(x,y)$$

$$(|L_x|^\alpha + \epsilon)^{-1} = \frac{1}{2}\Big((|L(x+1,y) - L(x,y)|^\alpha + \epsilon)^{-1} + (|L(x,y) - L(x-1,y)|^\alpha + \epsilon)^{-1}\Big)$$

$$\begin{aligned}
&\sum_{(x,y)} w(x,y) f(x,y) \\
&-\lambda \sum_{(x,y)} 1/2(|L(x+1,y) - L(x,y)|^\alpha + \epsilon)^{-1}\Big(f(x+1,y) + f(x-1,y) - 2f(x,y)\Big) \\
&-\lambda \sum_{(x,y)} 1/2(|L(x,y) - L(x-1,y)|^\alpha + \epsilon)^{-1}\Big(f(x+1,y) + f(x-1,y) - 2f(x,y)\Big) \\
&-\lambda \sum_{(x,y)} 1/2(|L(x,y+1) - L(x,y)|^\alpha + \epsilon)^{-1}\Big(f(x,y+1) + f(x,y-1) - 2f(x,y)\Big) \\
&-\lambda \sum_{(x,y)} 1/2(|L(x,y) - L(x,y-1)|^\alpha + \epsilon)^{-1}\Big(f(x,y+1) + f(x,y-1) - 2f(x,y)\Big) \\
&= \sum_{(x,y)} w(x,y) g(x,y)
\end{aligned}$$

single out each term

$f(x,y)$: $$\begin{aligned}&w(x,y)f(x,y)\\&+\lambda(|L(x+1,y)-L(x,y)|^\alpha+\epsilon)^{-1}f(x,y)\\&+\lambda(|L(x,y)-L(x-1,y)|^\alpha+\epsilon)^{-1}f(x,y)\\&+\lambda(|L(x,y+1)-L(x,y)|^\alpha+\epsilon)^{-1}f(x,y)\\&+\lambda(|L(x,y)-L(x,y-1)|^\alpha+\epsilon)^{-1}f(x,y)\end{aligned}$$

$g(x,y)$: $w(x,y)g(x,y)$

$f(x+1,y)$: $$\begin{aligned}&-\frac{\lambda}{2}(|L(x+1,y)-L(x,y)|^\alpha+\epsilon)^{-1}f(x+1,y)\\&-\frac{\lambda}{2}(|L(x,y)-L(x-1,y)|^\alpha+\epsilon)^{-1}f(x+1,y)\\&\approx-\lambda(|L(x+1,y)-L(x,y)|^\alpha+\epsilon)^{-1}f(x+1,y)\end{aligned}$$

Solving the Linear System

$$\mathbf{A} f = b$$

symmetric, sparse matrix

$$\mathbf{A}_{ij} = \begin{cases} -\lambda \left(\left| L_i - L_j \right|^{\alpha} + \varepsilon \right)^{-1} & j \in N_4(i) \\ w_i - \sum_{k \in N_4(i)} \mathbf{A}_{ik} & i = j \\ 0 & \text{otherwise} \end{cases}$$

$$b_i = w_i \, g_i$$

Fast Approximate Solution

preconditioned conjugate gradient $\mathbf{A} = \mathbf{L} + \mathbf{W}$

depends only on the original image

diagonal, affected by the specific constraints

$\mathbf{L} + \mathbf{I}$ compute the incomplete Cholesky decomposition only once

$U = VV^*$
lower triangular

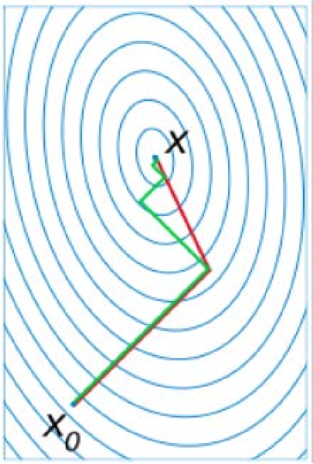
preconditioning $M^{-1}Ax = M^{-1}b$

$\lambda_{max}/\lambda_{min}$

M is symmetric positive definite
and is close to A

further speed-up: coarse-to-fine approach

Conjugate Gradient Method



finite steps

wikipedia

Conjugate Gradient Method as an Iterative Method

```
function x = conjgrad(A,b)
   x = 0; r = b; p = r;

   for k = 1:size(A, 1)
      a = (r'*r)/(p'*A*p);
      x = x + a*p;
      w = r;
      r = r - a*A*p;
      if ( sqrt(r'*r) < 1e-10 )
           break;
      end
      B = (r'*r)/(w'*w);
      p = r + B*p;
   end
return
```

residual

Gram-Schmidt

matrix –vector multiplication is easy

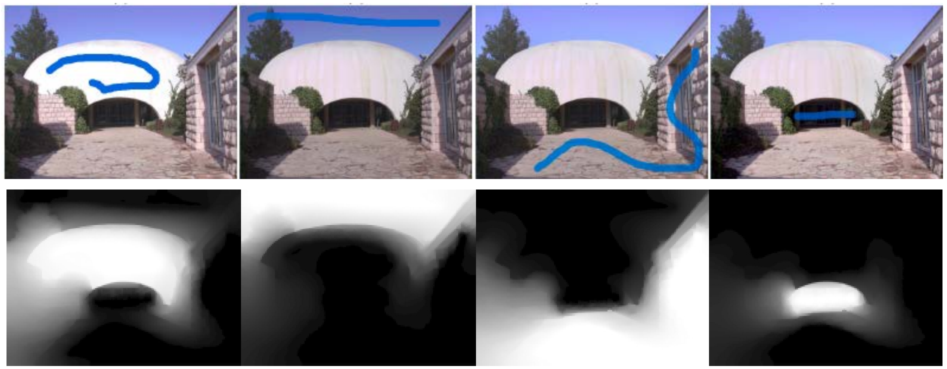
wikipedia

Basis Function Decomposition

- Applying different tonal parameters

$$\mathbf{A}f = b$$

$$w(\mathbf{x}) = \sum_l w_l(\mathbf{x}) \qquad b = \sum_l w_l\, g_l$$



pre-computed *influence function*

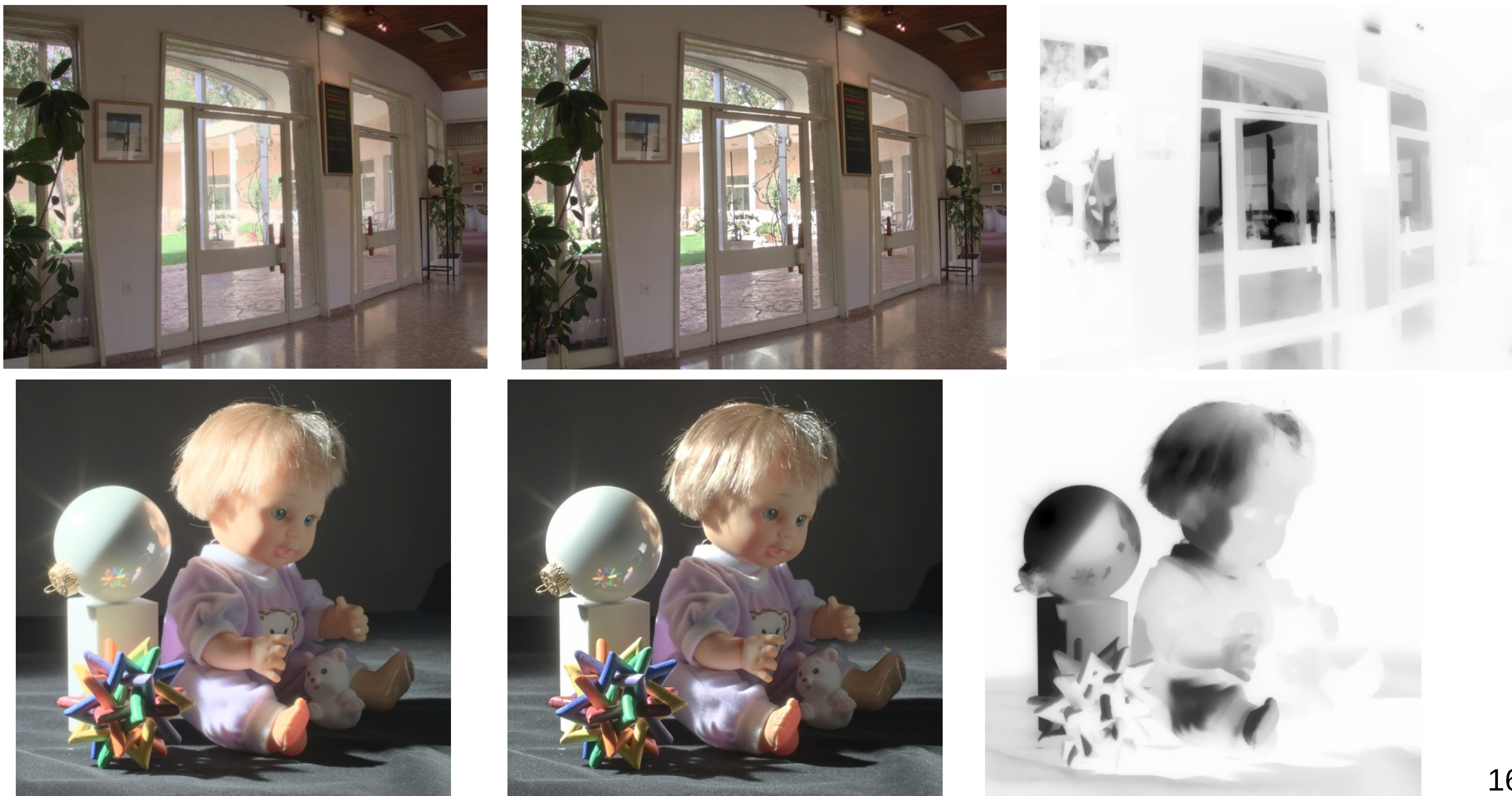
$$f_k = \sum_l g_{kl} u_l \qquad g'_{kl} \leftarrow g_{kl} + \Delta g_{kl}$$

$$f'_k = \mathbf{A}^{-1} b'_k = \mathbf{A}^{-1}(b_k + \Delta b_k) = f_k + \mathbf{A}^{-1} \Delta g_{kl} w_l = f_k + \Delta g_{kl} u_l$$

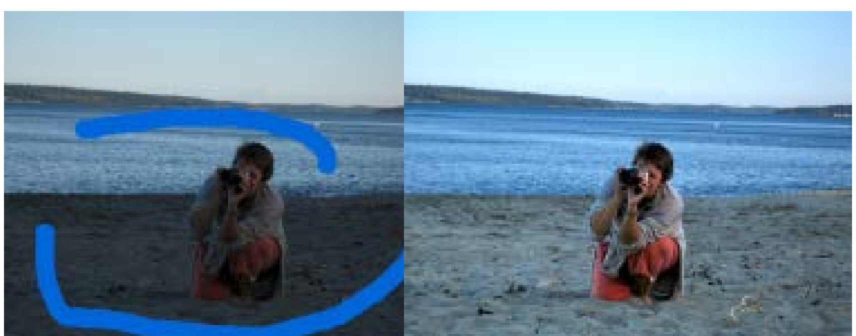
Automated Initialization

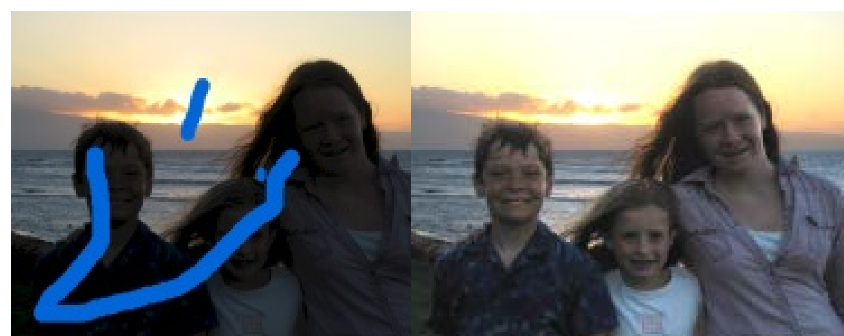
Zone system mapping median luminance in each zone

target exposure of each zone as soft constraints (w=0.07)



Other Applications





Another Related Paper on HDR Imaging

- Noise-Optimal Capture for High Dynamic Range Photography
  - Hasinoff, Durand, and Freeman
  - CVPR 2010
  - Using variable ISO settings