Color image processing problems in digital photography

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Outline

• High Dynamic Range (HDR) image creation in dynamic scenes
• Tone Mapping
• Demosaicking
HDR image creation in dynamic scenes
High contrasted scenes
High contrasted scenes

Radiance: light that concentrates at a single point.
HDR images: Outline

HDR image of static scenes

HDR images of dynamic scenes
  Registration of images with different $\Delta t$
  Image Fusion

HDR results and conclusions
$I \in [0, 1]$ : intensity value of Low Dynamic Range (LDR) image.
Notation

\[ I \in [0, 1] : \text{intensity value of Low Dynamic Range (LDR) image.} \]

\[ I \in (0, +\infty) : \text{Radiance value of a HDR image.} \]
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\( x = (x_0, y_0) \): pixel position in the domain \( \Omega \subset \mathbb{Z}^2 \).
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\[ \mathbf{x} = (x_0, y_0) : \text{pixel position in the domain } \Omega \subset \mathbb{Z}^2. \]

\[ \Delta t : \text{exposure time.} \]
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$\mathcal{I} \in (0, +\infty)$: Radiance value of a HDR image.

$x = (x_0, y_0)$: pixel position in the domain $\Omega \subset \mathbb{Z}^2$.

$\Delta t$: exposure time.

$f$: camera function: $I = f(\mathcal{I} \Delta t)$. 
HDR images of static scenes

\[ I_j \]
HDR images of static scenes

\[ \mathcal{I}_j = \frac{f^{-1}(I_j)}{\Delta I_j} \]
HDR images of static scenes

\[ I_j = \frac{f^{-1}(I_i)}{\Delta t_j} \]

\[ I = \sum_{i=0}^{N} \frac{w(I_i)I_i}{N} \]

[Mann and Picard, 1995]
[Debevec and Malik, 1997]
HDR image of dynamic scenes

$I_j$
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HDR image of dynamic scenes

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HDR image of dynamic scenes

Ghost artifacts
Main problem

Images differ in $\Delta t$: Different geometry and color.
State of the art

- Registration

- Fusion
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  - Median Threshold Maps [Ward, 2003, Grosch, 2006, Jacobs et al., 2008]

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    [Granados et al., 2010, Grosch, 2006, Heo et al., 2011, Jacobs et al., 2008, Khan et al., 2006]
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HDR image creation

- HDR image of static scenes
- HDR images of dynamic scenes
- HDR results and conclusions
Motion vs. Detail

Let us assume we have $f$
Motion vs. Detail

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$I_1$, $I_{ref}$
Motion vs. Detail

Let us assume we have $f$

$$\mathcal{I}_1$$

$$\mathcal{I}_{\text{ref}}$$

Radiometrically align $I_j$ with $I_{\text{ref}}$: $\tilde{I}_j = f(\mathcal{I}_j \Delta t_{\text{ref}})$
Image Matching Computation

Register each $\tilde{I}_j$ with $I_{ref}$ [Chambolle and Pock, 2011]
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Given an $\mathbf{x} \in \Omega_1$ that corresponds to $\mathbf{y} \in \Omega_{ref}$
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If $|\tilde{I}_1(x) - I_{ref}(y)| >> 0$
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Discard correspondences with a distance above \( \mu + \alpha \sigma \).
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Intensity vs. Gradient fusion
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Gradient-based fusion [Piella, 2009]:

• Create \( V : \Omega \mapsto \mathbb{R}^2 \).
  At \( x \), find the predominant gradient direction of the \( N \) corresponding pixels:

• Integrate using the Poisson Equation with Dirichlet boundary conditions.
Intensity vs. Gradient fusion

Gradient-based fusion [Piella, 2009]:

- Create $V : \Omega \mapsto \mathbb{R}^2$.

At $x$, find the predominant gradient direction of the $N$ corresponding pixels:

$$G_s(x) = \begin{pmatrix}
\sum_{j=0}^{N} s_j^2(x) \left( \frac{\partial \tilde{I}_j}{\partial x} \right)^2 & \sum_{j=0}^{N} s_j^2(x) \frac{\partial \tilde{I}_j}{\partial x} \frac{\partial \tilde{I}_j}{\partial y} \\
\sum_{j=0}^{N} s_j^2(x) \frac{\partial \tilde{I}_j}{\partial y} \frac{\partial \tilde{I}_j}{\partial x} & \sum_{j=0}^{N} s_j^2(x) \left( \frac{\partial \tilde{I}_j}{\partial y} \right)^2
\end{pmatrix}$$

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  \sum_{j=0}^{N} s_j^2(x) \frac{\partial \tilde{I}_j}{\partial y} \left(\frac{\partial \tilde{I}_j}{\partial y}\right)^2
  \end{array} \right)$$

  $$V(x) = \sqrt{\lambda \varepsilon(x)} \theta$$

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Gradient Fusion

This process can also be understood as the minimization of the energy:

$$\int_{\Omega^M} |\nabla \hat{I}(\mathbf{x}) - V(\mathbf{x})|^2 d\Omega^M.$$
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The difference between \( V \) and \( \nabla \hat{I}^* \): \textit{Residual Error}
Gradient Fusion: Residual Error
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Proposal: restrict more the solution with boundary conditions:
Gradient Fusion: Residual Error

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- Selected randomly pixels of the $I_{ref}$ with correspondences
Gradient Fusion: Residual Error

Proposal: restrict more the solution with boundary conditions:

- Selected randomly pixels of the $I_{ref}$ with correspondences
- Compute the weighted average of these points and set them Dirichlet boundary conditions.
Tone Mapped version of [Gallo et al., 2009]'s results.
HDR dynamic scenes: Conclusions

1. Radiometrical alignment: $\tilde{I}_j = f(I_j \Delta t_{\text{ref}})$
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Future work:
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Future work:
- Constraints related to exposure time and ISO values: Noise.
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Future work:
- Constraints related to exposure time and ISO values: Noise.
- Dealing with motion in over-exposed areas.
Perceptually-based tone mapping
High Dynamic Range images

Floating point images that represent the radiance of a given scene.
These images are not displayable in a regular Low Dynamic Range (LDR) display.
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Tone Mapping Operator

Function that maps an HDR into an LDR while preserving its overall appearance.
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In our own words, a TMO should deal with:

- the reproduction of contrast
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In our own words, a TMO should deal with:

- the reproduction of contrast
- the perception of color
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- Gradient-based approach: The main purpose is to properly shrink the gradient of the image.

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For a thorough review until 2005:

Two step approach inspired by the HVS:
Tone Mapping

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First stage:
- Visual Adaptation
- Contrast reproduction
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Tone Mapping: Outline

- Naka-Rushton based TMO
- Perceptually-based Tone Mapping
- Second stage
- TMO: Results and Conclusions
Visual Adaptation and the NR function

HVS can operate on a very large range: $10^{-6} \frac{cd}{m^2}$ to $10^6 \frac{cd}{m^2}$. 
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Visual Adaptation: photoreceptors adapt locally to the average of nearby retinal illumination value.
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Neuroscience experiments have shown that photoreceptors respond to light stimuli following the NR equation.
The NR equation for TM purposes:

The NR equation:

\[ r(I) = \frac{I}{I + I_s}, \]

where \( I_s \) is the semi saturation value associated to the adaptation level.
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Interesting mathematical properties:

- Monotonically increasing.
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Interesting mathematical properties:

- Monotonically increasing.
- Maps any range into [0, 1].
The NR equation for TM purposes

The NR equation:

\[ r(I) = \frac{I}{I + Is}, \]

where \( Is \) is the semi saturation value associated to the adaptation level.

Interesting mathematical properties:

- Monotonically increasing.
- Maps any range into [0, 1].
- Non-linear behavior.
Modified NR equation

If $I_s$ constant, then ‘saturation catastrophe’ [Shapley and Enroth-Cugell, 1984].
Modified NR equation

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$$r(I) = \frac{I}{I + I_s} \quad \rightarrow \quad rf(I) = \frac{I}{I + fI_s(I)}$$
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How to apply the modified NR equation to HDR images?
Notation

\[ \vec{I} : \Omega \rightarrow (0, \infty)^3 \] Radiance map representing the input HDR image.
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\( \vec{I} : \Omega \to (0, \infty)^3 \) Radiance map representing the input HDR image.

\( I_c : \) generic value of scalar chromatic component \( c \in \{R, G, B\} \).
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\( \vec{I} : \Omega \rightarrow (0, \infty)^3 \) Radiance map representing the input HDR image.

\( I_c : \text{generic value of scalar chromatic component } c \in \{R, G, B\} \).

\( I_c(x) : \text{component } c \text{ of the color vector at spatial position } x \in \Omega \).
Notation

\( \vec{I} : \Omega \rightarrow (0, \infty)^3 \) Radiance map representing the input HDR image.

\( \mathcal{I}_c \): generic value of scalar chromatic component \( c \in \{R, G, B\} \).

\( \mathcal{I}_c(x) \): component \( c \) of the color vector at spatial position \( x \in \Omega \).

\[ \lambda(x) = \frac{\mathcal{I}_R(x) + \mathcal{I}_G(x) + \mathcal{I}_B(x)}{3} \] luminance value at \( x \)
Modified NR eq. and HDR images

\( I_s \) is associated to the background intensity.
Modified NR eq. and HDR images

$I_s$ is associated to the background intensity.
Identify it with an average ($\mu$):

$$r_f(I) = \frac{I}{I + f_I s(I)}$$
Modified NR eq. and HDR images

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Identify it with an average (\( \mu \)):

\[
rf(I) = \frac{I}{I + f\mu(I)}
\]
\(I_s\) is associated to the background intensity.

Identify it with an average \((\mu)\):

\[
rf(I) = \frac{I}{I + f_{\mu}(I)}
\]

We need to define \(I\) and \(f_{\mu}\) in the context of HDR images.
Modified NR equation: Color

Let us fix $f_\mu(I) = \mu$. 

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Color image processing problems in digital photography
Modified NR equation: Color

Let us fix $f_\mu(I) = \mu$.

\[
\begin{align*}
    r_{\eta f}(I_c(x)) &= \left( \frac{I_c(x)}{\lambda(x)} \right)^\eta r_f(\lambda(x)) \\
    r_f(I_c(x)) &= \frac{I_c(x)}{I_c(x) + f_\mu(\lambda(x))} \\
    r_f(I_c(x)) &= \frac{I_c(x)}{I_c(x) + f_\mu(I_c(x))}
\end{align*}
\]

[Tumblin and Turk, 1999]  
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[Reinhard and Devlin, 2005]
Perceptual contrast
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Weber-Fechner (WF) contrast law: \( \frac{1}{k} \Delta s = \frac{\Delta \lambda}{\lambda + m} \),
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- \( \Delta s \): change in sensation.
- \( \Delta \lambda \): Just Noticeable Difference (JND).
Perceptual contrast

**Weber-Fechner (WF) contrast law:** \( \frac{1}{k} \Delta s = \frac{\Delta \lambda}{\lambda + m} \),

- \( \Delta s \): change in sensation.
- \( \Delta \lambda \): Just Noticeable Difference (JND).
- \( k, m \): constant values.
Perceptual contrast
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The goal: \( \frac{\Delta \lambda}{\lambda + m} = \frac{1}{k} \Delta s \)
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- integrating: \[ s(\lambda) = C + k \log(m + \lambda) \]
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To obtain \( f_\mu(\lambda) \), let us rewrite: \( r_f(\lambda) = \frac{\lambda}{\lambda + f_\mu(\lambda)} \)
Perceptual contrast

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To obtain \( f_\mu(\lambda) \), let us rewrite: \[ r_f(\lambda) = \frac{\lambda}{\lambda + f_\mu(\lambda)} \]

Equating \( r_f \) and \( s \), using \( r_f(\mu) = \frac{1}{2} \) (the Grey world assumption):

\[
f_\mu(\lambda) = -\lambda + \frac{\lambda}{\frac{1}{2} + k \log\left(\frac{m + \lambda}{m + \mu}\right)}
\]
NR eq. and HDR color images

Imposing $s(\lambda_{\text{min}}) = 0$ and $s(\lambda_{\text{max}}) = 1$: 
NR eq. and HDR color images

Imposing $s(\lambda_{\text{min}}) = 0$ and $s(\lambda_{\text{max}}) = 1$:

$$k = \frac{1}{\log\left(\frac{m + \lambda_{\text{max}}}{m + \lambda_{\text{min}}}\right)}, \quad m = \frac{\mu^2 - \lambda_{\text{max}} \lambda_{\text{min}}}{\lambda_{\text{max}} + \lambda_{\text{min}} - 2\mu}$$
NR eq. and HDR color images

Imposing $s(\lambda_{\text{min}}) = 0$ and $s(\lambda_{\text{max}}) = 1$:

$$k = \frac{1}{\log\left(\frac{m+\lambda_{\text{max}}}{m+\lambda_{\text{min}}}ight)}, \quad m = \frac{\mu^2 - \lambda_{\text{max}} \lambda_{\text{min}}}{\lambda_{\text{max}} + \lambda_{\text{min}} - 2\mu}$$

Final equation:

$$r(I_c(x)) = \frac{I_c(x)}{I_c(x) - \lambda(x) + \frac{\lambda(x)}{\frac{1}{2} + k \log\left(\frac{m+\lambda(x)}{m+\mu}\right)}}$$
Histogram distribution and $\mu$
Histogram distribution and $\mu$
Histogram distribution and $\mu$

Multi-modal histogram images are not well represented by a sole average
A multi-modal approach

We propose a multimodal approach:
A multi-modal approach

We propose a multimodal approach:

- Estimate of the modes center with Gaussian Mixture Models
A multi-modal approach

We propose a multimodal approach:

- Estimate of the modes center with Gaussian Mixture Models
- We define a NR function for each mode
A multi-modal approach

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• Concatenate the NR functions linearly
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A multi-modal approach

Obtaining

\[ f_{rG}(\lambda) = -\lambda + \frac{\lambda}{r_G(\lambda)} \]

Finally, we extend the formula to color images:

\[ r_G(I_c(x)) = \frac{I_c(x)}{I_c(x) + f_{rG}(\lambda)} \]
One mode vs several modes
One mode vs several modes
One vs several modes
One vs several modes
Revisiting Tone Mapping
Revisiting Tone Mapping

"A TMO should reproduce the sensation produced in the observer by the real scene."
Revisiting Tone Mapping

"A TMO should reproduce the sensation produced in the observer by the real scene."

The context of TM is the Psychophysics field, not in Neuroscience.
Revisiting the NR function

The NR function models the response of one single living cell in lab conditions.

The communication between the retina and the brain is complex.
The NR function models the response of *one single* living cell in lab conditions.

The communication between the retina and the brain is complex.

The NR function is not representative of contrast perception.
Revisiting the NR function

\[ s(\mathcal{I}) = k \log(\mathcal{I} + m) \]

\[ r(\mathcal{I}) = \frac{\mathcal{I}}{\mathcal{I} + \mu} \]
Revisiting the WF contrast law

The WF contrast law: \[ \frac{\Delta \lambda}{\lambda + m} = \frac{1}{k} \Delta s \]
The WF contrast law: \[ \frac{\Delta \lambda}{\lambda + m} = \frac{1}{k} \Delta s \]

For static conditioning stimuli, the response extends indefinitely.

Figure adapted from [Shevell, 1977].
Revisiting the WF contrast law

The WF contrast law: \[
\frac{\Delta \lambda}{\lambda + m} = \frac{1}{k} \Delta s
\]

For static conditioning stimuli, the response extends indefinitely.

For pulsated stimuli, the cone response saturates.

Figure adapted from [Shevell, 1977].
Revisiting the WF contrast law
Revisiting the WF contrast law

Saccadic movements to gather details.
Revisiting the WF contrast law

Saccadic movements to gather details.

The stimuli fields can be understood as *pulsed* [Dunn et al., 2007]

In real-world images, the curve should saturate.
Range compression step

![Chart showing range compression step with different curves representing Naka-Rushton, Weber-Fechner, Scaled Weber-Fechner, and Proposed Curve. The x-axis represents log_{10} L, and the y-axis represents TMO Processed.]
Range compression step

\[ t(I) = \begin{cases} 
    k \log(I + m) + C, & I \leq I_M \\
    \frac{I^n}{I^n + I_s^n}, & I > I_M 
\end{cases} \]
Tone Mapping

Two step approach inspired by the HVS:

First stage:
- Visual Adaptation
- Contrast reproduction

Second stage: Variational method [Palma-Amestoy et al., 2009] for:
- Local contrast enhancement
- Chromatic adaptation
Tone Mapping

Two step approach inspired by the HVS:

First stage:
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Second stage: Variational method [Palma-Amestoy et al., 2009] for:
- Local contrast enhancement
- Chromatic adaptation
Second stage

Local contrast enhancement
Second stage

Local contrast enhancement

![Local contrast enhancement graph](image)
Second stage

Local contrast enhancement

![Graphs showing local contrast enhancement](image-url)
Second stage

Local contrast enhancement

Chromatic adaptation

Sira Ferradans Ramonde

Color image processing problems in digital photography
Second stage

Local contrast enhancement

Chromatic adaptation

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Color image processing problems in digital photography
Second stage

Local contrast enhancement

Chromatic adaptation

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Color image processing problems in digital photography
Second stage

Minimize:

\[ E(I) = -\alpha C_w(I) + \beta D_\mu(I) + \gamma A_{I_0}(I) \]
Second stage

Minimize:

\[ E(I) = -\alpha C_w(I) + \beta D_\mu(I) + \gamma A_{I_0}(I) \]

Contrast term: \[ C_w(I) = \int \int_{\Omega^2} w(x, y)|I(x) - I(y)|dx\,dy \]
Second stage

Minimize:

\[ E(I) = -\alpha C_w(I) + \beta D_{\mu}(I) + \gamma A_{I_0}(I) \]

Contrast term: \( C_w(I) = \int \int_{\Omega^2} w(x, y) |I(x) - I(y)| \, dx \, dy \)

Dispersion term: \( D_{\mu}(I) = \int_{\Omega} (I(x) - \mu)^2 \, dx \)
Second stage

Minimize:

\[ E(I) = -\alpha C_w(I) + \beta D_{\mu}(I) + \gamma A_{I_0}(I) \]

Contrast term: \( C_w(I) = \int \int_{\Omega^2} w(x, y)|I(x) - I(y)|dxdy \)

Dispersion term: \( D_{\mu}(I) = \int_{\Omega} (I(x) - \mu)^2 dx \)

Attachment term: \( A_{I_0}(I) = \int_{\Omega} (I(x) - I_0(x))^2 dx \)
Second stage
Second stage

Sira Ferradans Ramonde

Color image processing problems in digital photography
Second stage
Results

Quality measure by [Aydin et al., 2008]
Results

Quality measure by [Aydin et al., 2008]

- Grey: no error
- Red: contrast reversal
- Green: loss of visible contrast
- Blue: amplification of contrast
Results

Quality measure by [Aydin et al., 2008]

- Grey: no error
- Red: contrast reversal
- Green: loss of visible contrast
- Blue: amplification of contrast

The saturation of each color indicates the magnitude.
Tone Mapping: Results

We will compare to four methods from the state of the art:

1. [Drago et al., 2003]
2. [Mantiuk et al., 2006]
3. [Pattanaik et al., 2000]
4. [Reinhard and Devlin, 2005]
Tone Mapping: Results

[Drago et al., 2003] [Mantiuk et al., 2006] [Pattanaik et al., 2000] [Reinhard and Devlin, 2005]

Proposed method

Original image from first row courtesy of ILM.
Tone Mapping: Results

[Drago et al., 2003] [Mantiuk et al., 2006] [Pattanaik et al., 2000] [Reinhard and Devlin, 2005]

Proposed method

Original image from first row courtesy of ILM.
## Tone Mapping: Results

<table>
<thead>
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<th>Methods</th>
<th>Reverse</th>
<th>Loss</th>
<th>Amplification</th>
<th>Total</th>
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<td>4</td>
<td>4.9</td>
<td>37.32</td>
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<td>[Fattal et al., 2002]</td>
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<td>0.64</td>
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<td>[Mantiuk et al., 2006]</td>
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<td>[Pattanaik et al., 2000]</td>
<td>6.41</td>
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<td>[Reinhard et al., 2002]</td>
<td>5.5</td>
<td>4.92</td>
<td>38.06</td>
<td>48.48</td>
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<td>[Reinhard and Devlin, 2005]</td>
<td>5.81</td>
<td>3.71</td>
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<tr>
<td>Our TMO</td>
<td>0.74</td>
<td>9.23</td>
<td>16.61</td>
<td>26.58</td>
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</table>
Tone Mapping: Conclusions

Proposed method implements:
Proposed method implements:

- WF law for every color channel independently
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- WF law for every color channel independently
- Visual adaptation
Tone Mapping: Conclusions

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Results compare favorably to the state of the art according to the contrast measure of [Aydin et al., 2008]
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Connection between pulsed-light background experiments and contrast perception in HDR scenes.
Tone Mapping: Future Work

Need of quality measure of color reproduction
Tone Mapping: Future Work

Need of quality measure of color reproduction

Extension to video
Tone Mapping: Future Work

Need of quality measure of color reproduction

Extension to video

Set automatically the parameters
Demosaicking
Demosaicking: Outline

Bayer Color Filter Array

Geometry-based Demosaicking

Demosaicking: Results and conclusions
Bayer Color Filter Array
Demosaicking

Bayer Color Filter Array

Bayer Color Filter array
Demosaicking

Bayer Color Filter Array

Demosaicking:

Bayer Color Filter array
Demosaicking

Bayer Color Filter Array

Demosaicking:

• data obtained from a camera with a color filter array
Demosaicking

Bayer Color Filter array

Demosaicking:

- data obtained from a camera with a color filter array
- interpolation process
Demosaicking:

- data obtained from a camera with a color filter array
- interpolation process
- goal: obtain a full color image
Demosaicking STAR

Robust estimation of the direction of the edges and interpolation along them

[Tsai and Song, 2007, Menon et al., 2007, Li, 2005, Chung and Chan, 2006, Hirakawa and Parks, 2005]
Demosaicking STAR

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[Tsai and Song, 2007, Menon et al., 2007, Li, 2005, Chung and Chan, 2006, Hirakawa and Parks, 2005]

[Buades et al., 2007] averaging pixels with similar neighborhood
Demosaicking STAR

Robust estimation of the direction of the edges and interpolation along them

[Tsai and Song, 2007, Menon et al., 2007, Li, 2005, Chung and Chan, 2006, Hirakawa and Parks, 2005]

[Buades et al., 2007] averaging pixels with similar neighborhood

[Mairal et al., 2008] interpolation based on image dictionary of patches
Level lines and color

All the geometric information of an image is contained in its family of level lines [Caselles et al., 1999].
Level lines and color

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Level lines and color

Assumption: The three color channels share the family of level lines [Caselles et al., 2002].
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Demosaicking: Outline

- Bayer Color Filter Array
- Geometry-based Demosaicking
- Demosaicking: Results and conclusions
Estimating the level-line direction
Estimating the level-line direction
Estimating the level-line direction

Find the optimal *global* match between pixels in diagonal $n - 1$ and $n + 1$. 
Estimating the level-line direction

Find the optimal \emph{global} match between pixels in diagonal $n - 1$ and $n + 1$.

- The level lines never cross.
Estimating the level-line direction

Find the optimal *global* match between pixels in diagonal $n - 1$ and $n + 1$.

- The level lines never cross.
- The matching function is non-decreasing.
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- The global solution is a combination of the solution of the subproblems.
Estimating the level-line direction

Find the optimal *global* match between pixels in diagonal $n - 1$ and $n + 1$.

- The level lines never cross.
- The matching function is non-decreasing.
- The global solution is a combination of the solution of the subproblems.

Optimization problem can be solved with dynamic programming

[Cox et al., 1996]
Estimating the level-line direction

Cost of matching two pixels $p$ in diagonal $n - 1$ and $q$ in $n + 1$: 
Estimating the level-line direction

Cost of matching two pixels $p$ in diagonal $n - 1$ and $q$ in $n + 1$:

- Spatial distance between them: $|p - q|$
Estimating the level-line direction

Cost of matching two pixels $p$ in diagonal $n-1$ and $q$ in $n+1$:

- Spatial distance between them: $|p - q|
- A distance of their neighborhood: $D(p, q)$
Cost of matching two pixels $p$ in diagonal $n - 1$ and $q$ in $n + 1$:

- Spatial distance between them: $|p - q|$

- A distance of their neighborhood: $D(p, q)$

\[
\text{cost}(p, q) = (\alpha + \beta|p - q|)D(p, q)
\]
Interpolation
Interpolation
Interpolation
Interpolation

**Green plane**: Pixel $a$ in a R position in between $p, q$: 
Interpolation

**Green plane**: Pixel $a$ in a R position in between $p, q$:

\[
\hat{I}_G(a) = \frac{I_G(p) + I_G(q)}{2} + \begin{cases} 
\frac{(I_R(a) - I_R(a-(0,2)) + (I_R(a) - I_R(a+(0,2)))}{4} & \text{if } \bar{pq} \text{ is horizontal} \\
\frac{(I_R(a) - I_R(a-(2,0)) + (I_R(a) - I_R(a+(2,0)))}{4} & \text{if } \bar{pq} \text{ is vertical} \\
\frac{(4I_R(a) - I_R(a-(0,2)) - I_R(a+(0,2))) - I_R(a-(2,0)) - I_R(a+(2,0)))}{8} & \text{otherwise}
\end{cases}
\]
Green plane: Pixel \( a \) in a R position in between \( p, q \):

\[
\hat{I}_G(a) = \frac{I_G(p) + I_G(q)}{2} + \begin{cases} 
\frac{(I_R(a) - I_R(a - (0, 2)) + (I_R(a) - I_R(a + (0, 2))))}{4} \\
\frac{(I_R(a) - I_R(a - (2, 0)) + (I_R(a) - I_R(a + (2, 0))))}{4} \\
\frac{(4I_R(a) - I_R(a - (0, 2)) - I_R(a + (0, 2)))}{8} - \frac{I_R(a - (2, 0)) - I_R(a + (2, 0))}{8} 
\end{cases}
\]

if \( \vec{pq} \) is horizontal  
if \( \vec{pq} \) is vertical  
otherwise

Assumption: \( D^2_x I_G(a) = D^2_x I_R(a) \)
Green plane: Pixel \( a \) in a R position in between \( p, q \):

\[
\hat{I}_G(a) = \frac{I_G(p) + I_G(q)}{2} + \begin{cases} 
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\frac{(4I_R(a) - I_R(a - (0,2)) - I_R(a + (0,2))))}{8} - \frac{I_R(a - (2,0)) - I_R(a + (2,0)))}{8} & \text{otherwise}
\end{cases}
\]

Assumption: \( D_\chi^2 I_G(a) = D_\chi^2 I_R(a) \)

Full color image: Pixel \( a \) in a G position:
Interpolation

Green plane: Pixel \(a\) in a R position in between \(p, q\):

\[
\hat{I}_G(a) = \frac{I_G(p) + I_G(q)}{2} + \begin{cases}
\frac{(I_R(a) - I_R(a - (0, 2)) + (I_R(a) - I_R(a + (0, 2)))}{4} & \text{if } \bar{pq} \text{ is horizontal} \\
\frac{(I_R(a) - I_R(a - (2, 0)) + (I_R(a) - I_R(a + (2, 0)))}{4} & \text{if } \bar{pq} \text{ is vertical} \\
\frac{(4I_R(a) - I_R(a - (0, 2)) - I_R(a + (0, 2)))}{8} & \text{otherwise}
\end{cases}
\]

Assumption: \(D^2_\lambda I_G(a) = D^2_\lambda I_R(a)\)

Full color image: Pixel \(a\) in a G position:

\[
\hat{I}_R(a) = I_G(a) + \sum_{w \in \Psi_R} \frac{I_R(a + w) - \hat{I}_G(a + w)}{N}
\]

Hue-based interpolation technique [Gunturk et al., 2005]
Core Algorithm

1. Compute full color image from the $+45$ diagonals
Core Algorithm

1. Compute full color image from the $+45$ diagonals
2. Compute full color image from the $-45$ diagonals
Core Algorithm

1. Compute full color image from the $+45$ diagonals
2. Compute full color image from the $-45$ diagonals
3. Self-similarity measure: select the pixel with the minimum color difference with its neighborhood.
Complete algorithm
Complete algorithm

Distance measures:

- **G-comparison:**

\[
D_1(p, q) = \frac{1}{N} \sqrt{\sum_{w \in \Psi_G} (I_G(p + w) - \bar{I}_{G,p} - I_G(q + w) + \bar{I}_{G,q})^2}
\]
Complete algorithm

Distance measures:

- **G-comparison:**
  \[
  D_1(p, q) = \frac{1}{N} \sqrt{\sum_{w \in \Psi_G} (I_G(p + w) - \bar{I}_{G,p} - I_G(q + w) + \bar{I}_{G,q})^2}
  \]

- **Interchannel and interpixel comparison:**
  \[
  D_2(p, q) = \frac{IID_h(p, q) + IID_v(p, q)}{2}
  \]
Complete algorithm

Distance measures:

- **G-comparison:**
  \[ D_1(p, q) = \frac{1}{N} \sqrt{\sum_{w \in \Psi} (I_G(p + w) - \bar{I}_{G,p} - I_G(q + w) + \bar{I}_{G,q})^2} \]

- **Interchannel and interpixel comparison:**
  \[ D_2(p, q) = \frac{IID_h(p, q) + IID_v(p, q)}{2} \]

- **3D-comparison:**
  \[ D_3(p, q) = \frac{1}{N} \sum_{w \in \Psi} \sum_{c \in R, G, B} [I_c(p + w) - \bar{I}_{c,p} - I_c(q + w) + \bar{I}_{c,q}]^2 \]
Results

Original Images
Results

Results with Geometry based Demosaicking
State of the art

1. [Lian et al., 2007]
2. [Zhang and Wu, 2005]
3. [Chung and Chan, 2006]
State of the art

Original image

Geometry based Demosaicking

[Lian et al., 2007] [Zhang and Wu, 2005] [Chung and Chan, 2006]
### Numerical Results

<table>
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<td>Std</td>
<td>2.72</td>
<td>2.64</td>
<td>2.62</td>
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</table>
Geometry-based Demosaicking: Conclusions

We have proposed a method for global level-line estimation.
Geometry-based Demosaicking: Conclusions

We have proposed a method for global level-line estimation. Compares favorably to the state of the art.
Geometry-based Demosaicking: Conclusions

We have proposed a method for global level-line estimation. Compares favorably to the state of the art.

Original  Result

Zipper effect on saturated colors.
Thank you for your attention, Questions ?
The presented work has partially been published in the following articles:


A first-order primal-dual algorithm for convex problems with applications to imaging.  

Color demosaicing using variance of color differences.  

A maximum likelihood stereo algorithm.  
*Computer Vision and Image Understanding*, 63(3):542–567.

Recovering high dynamic range radiance maps from photographs.


Fast and robust high dynamic range image generation with camera and object movement.

Demosaicking: color filter array interpolation.

Ghost-free high dynamic range imaging.

Adaptive homogeneity-directed demosaicing algorithm.


A visibility matching tone reproduction operator for high dynamic range scenes.

