Freehand HDR Imaging of Moving Scenes with Simultaneous Resolution Enhancement

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1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

High Dynamic Range (HDR) Imaging

(e.g. Debevec and Malik, SIGGRAPH 1997)

three images of an exposure series
(courtesy of Paul Debevec)

tone mapped HDR result

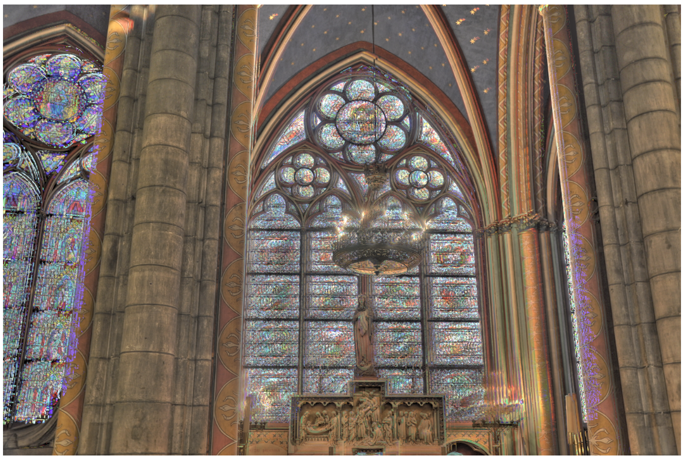
- **Given: exposure series** (set of images with varying exposure times)
- **Wanted: scene radiances (HDR image)**
  - overcome low dynamic range of sensor ⇒ details in dark and bright regions

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

HDR Imaging in Practice

- **Problem:** HDR methods require **aligned** (registered) exposure series
  - often violated in practice : camera shake, moving objects

freehand
exposure series



tone mapped HDR result

⇒ Need for alignment strategies

Motivation (2)

M I A
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21 22

HDR Imaging in Practice

- **Problem:** HDR methods require **aligned** (registered) exposure series
  - often violated in practice : camera shake, moving objects

freehand
exposure series

tone mapped HDR result **after alignment**

⇒ Need for alignment strategies

Structure

- Existing Alignment Strategies
- **PART I :** Optic Flow-based Alignment
- **PART II :** Joint Super-resolution and HDR Reconstruction
- Conclusions and Outlook

Existing Alignment Strategies

- Alignment requires to find **displacements** between images
- Common matching criteria fail due to varying exposures
- Different strategies have been proposed:
  - **global** transformation from mean threshold bitmaps *(Ward, JGT 2003)*
  - **homography** from feature matches *(Tomaszewska and Mantiuk, WSCG 2007 / Hugin)*

    $\Rightarrow$ both cannot handle moving objects, arbitrary camera motions
  - **global** alignment, refined by **local** optic flow *(Kang et al., SIGGRAPH 2003)*

    $\Rightarrow$ heavily depends on global initialisation, no refinement in flat regions
  - **block matching** with exposure-invariant score *(Menzel and Guthe, VMV 2007)*

    $\Rightarrow$ suffers from artefacts due to missing smoothness assumption

PART I

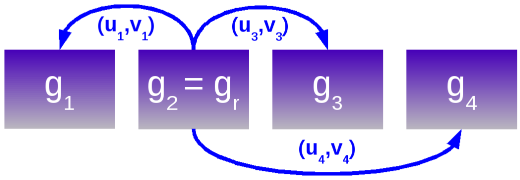
Optic Flow-based Alignment

Optic Flow-based Alignment

- **Idea:** Adapt energy-based optic flow method for estimating displacements
- Many advantages:
  - **dense** displacement fields (important for moving objects)
  - highly **accurate**
  - **robust** under outliers (noise, saturation, occlusions)
  - explicit **smoothness** assumption (fill in information)
  - **efficient** sequential and parallel implementations

Energy-based Optic Flow

- **Given:** exposure series $g_k(i,j)$, with $k = 1, \ldots, m$ for m exposures
- **Wanted:** displacement fields (u_k, v_k) between g_k and **reference image** g_r



- **Strategy:** Find displacements (u_k, v_k) by minimising the energy

$$E(u_k, v_k) \;=\; \sum_{\text{pixels}} \Big[D(u_k, v_k) + \alpha \, S(\boldsymbol{\nabla} u_k, \boldsymbol{\nabla} v_k) \Big]$$

  - data term $D(u_k, v_k)$ models constancy assumption on image features
  - smoothness term $S(\boldsymbol{\nabla} u_k, \boldsymbol{\nabla} v_k)$ penalises fluctuations in displacements

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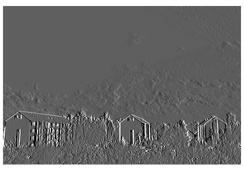
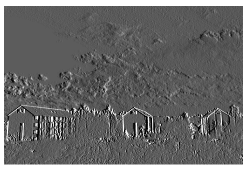
Modelling the Data Term

- **Idea:** Handle varying exposure times by matching image edges
  - gradient $\boldsymbol{\nabla} g = (\mathcal{D}_x \, g, \, \mathcal{D}_y \, g)^\top$ should remain constant under displacements
  - does not require to operate on radiances $\Rightarrow$ no camera calibration needed


g_1 $(t = 1/30$ s$)$


g_3 $(t = 1/80$ s$)$


$\mathcal{D}_x \, g_1$


$\mathcal{D}_x \, g_3$

- Corresponding data term:

$$D(u_k, v_k) = \Psi\Big(\big| \boldsymbol{\nabla} g_k(i{+}u_k, j{+}v_k) - \boldsymbol{\nabla} g_r(i,j) \big|^2 \Big)$$

  - sub-quadratic penaliser $\Psi(s^2) = \sqrt{s^2 + \varepsilon^2}$ reduces influence of outliers

- **Extension:** normalisation to prevent weighting by image gradients

Modelling the Smoothness Term

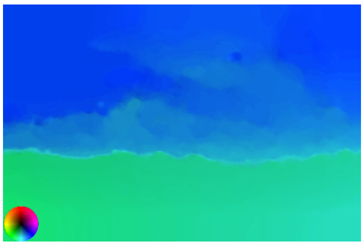
- Smoothness term fills in displacements in flat regions, e.g. saturations
- Data term gives no information as image gradients vanish
- Also regularises the displacements by penalising large gradients:

$$S\left(\boldsymbol{\nabla} u_k, \boldsymbol{\nabla} v_k\right) = \Psi\Big(\left|\boldsymbol{\nabla} u_k\right|^2 + \left|\boldsymbol{\nabla} v_k\right|^2\Big)$$

  - sub-quadratic penaliser $\Psi(s^2) = \sqrt{s^2 + \varepsilon^2}$ gives sharp displacement edges

g_3 (reference)

g_4



dense flow from g_3 to g_4

Comparison to Literature

- Real world, freehand exposure series (severe camera shake, moving clouds)

g_1

g_3 (reference)

g_5

M I A 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Comparison to Literature

- Tone mapped HDR reconstructions after alignment with different strategies

global *(Ward, JGT 03)*

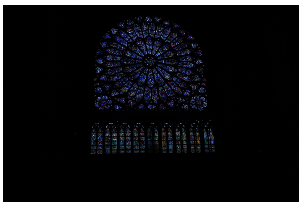
homography *(Hugin)*

NCC *(Menzel and Guthe, VMV 07)*

our result

More Results (using fixed parameters)

- Real world, freehand exposure series (*Window*)



g_1

g_4 (reference)

g_7

no alignment

our result

M I A
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

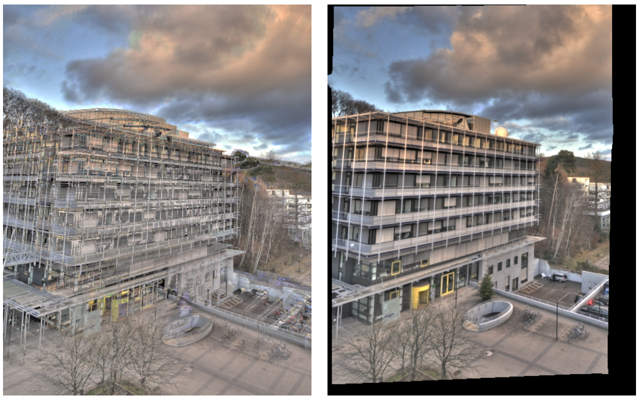
Optic Flow-based Alignment (8)

M I A
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

More Results (using fixed parameters)

- Real world, freehand exposure series (*MPI*)

g_1 g_3 (reference) g_5



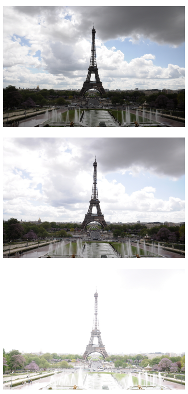
no alignment our result

Optic Flow-based Alignment (9)

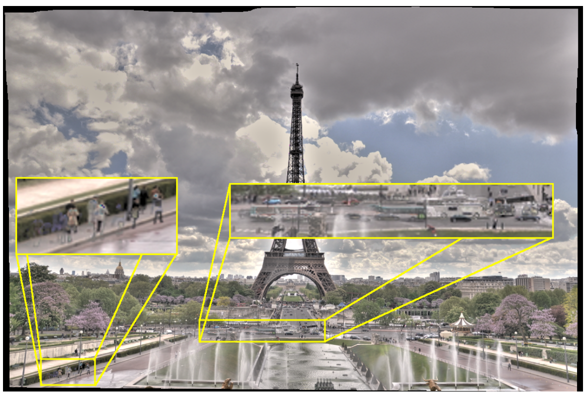
M I A
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Limitations

- Minimisation of energy proceeds in a coarse-to-fine warping scheme
- Naturally yields problems with estimating large displacements of small objects



g_1, g_2, g_4



result, insets show problems with small objects

PART II

Joint Super-resolution and HDR Reconstruction

Joint Super-resolution and HDR Reconstruction

- Optic flow-based alignment: dense displacements with **subpixel precision**
- Opens the door for **super-resolution** (SR) techniques
- **Idea:** Combine SR and HDR methods in a **joint SR-HDR** method
- Turns the problem of displacements in the exposure series into an advantage

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Energy-based Joint SR-HDR Reconstruction

- **Given:** low-resolution exposure series g_k and zoom factor $z > 1$
- **Wanted:** Super-resolved radiances F
- **Strategy:** Find F by minimising the energy

$$E(F) = \sum_{\text{pixels}} \Big[D(F) + \lambda \, S(\boldsymbol{\nabla} F) \Big]$$

  - data term $D(F)$ combines SR and HDR observation models
  - smoothness term $S(\boldsymbol{\nabla} F)$ fills in information (saturation, no LR information)

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Towards a Joint SR-HDR Data Term

- **Super-resolution observation model:**

$$RBW_k G = g_k$$

  - W_k : warping by displacements
  - B : blurring due to optical blur, motion blur, sensor PSF
  - R : restriction (downsampling) to LR grid

- **HDR observation model:**

$$f = \frac{I(g_k)}{t_k}$$

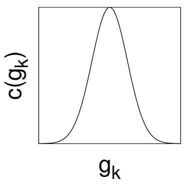
  - I : inverse camera response function
  - t_k : exposure time

Joint SR-HDR Data Term

- **Joint SR-HDR data term**

$$D(F) = \sum_{\text{exposures } k} c(g_k)\ \Psi\left(\left(\underbrace{RBW_k}_{\text{SR}}\ F - \underbrace{\frac{I(g_k)}{t_k}}_{\text{HDR}}\right)^2\right)$$

- $c(g_k)$: HDR weighting function reducing influence of less reliable (dark and bright) pixels



- $\Psi(s^2) = \sqrt{s^2 + \varepsilon^2}$: sub-quadratic penaliser reducing influence of outliers

A Novel Anisotropic Smoothness Term

- Smoothness term is important to fill in missing information, e.g. at saturations
- **Anisotropic smoothness term** adapts smoothing direction to image structures
  - strong smoothing along edges (quadratic penalisation)
  - reduced smoothing across edges (sub-quadratic penalisation)
- Edge direction: consider upsampled HDR reconstruction of exposure series
  - gives vector $\mathbf{v}_1$ pointing across edges, $\mathbf{v}_2$ pointing along edges
- Proposed smoothness term

$$S(\boldsymbol{\nabla} F) = \underbrace{\Psi\left(\left(\mathbf{v}_1^\top \boldsymbol{\nabla} F\right)^2\right)}_{\text{across}} + \underbrace{\left(\mathbf{v}_2^\top \boldsymbol{\nabla} F\right)^2}_{\text{along}}$$

with Charbonnier penaliser $\Psi\left(s^2\right) = 2\,\mu^2 \sqrt{1 + (s^2/\mu^2)}$

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1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Results (using fixed parameters except for λ)

- Real world, freehand exposure series (*Street*)

g_1

g_6 (reference)

g_{12}

pure HDR

joint SR-HDR
$\lambda = 0.4, z = 2$

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1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Results (using fixed parameters except for λ)

- Real world, freehand exposure series (*Flower*)

g_1

g_4 (reference)

g_8

pure HDR

joint SR-HDR
$\lambda = 0.6, z = 2$

Take Home Messages

- Modern **optic flow** methods are well-suited for **aligning HDR exposure series**
- Sub-pixel accuracy of displacement fields enables **resolution enhancement**

Future Work

- Address large displacements of small objects
- Port to mobile platforms (iPhone, Android phone)

Thank You!

- More information:

  `http://www.mia.uni-saarland.de/Research/SR-HDR`