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> Special thanks to: Karol Myszkowski, MPI Informatik, Germany



Introduction: The Problem

Longratio

E traggetio



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Introduction: Outline

- Dynamic Range and Color Retargeting (~70 mins):
 Rafał Mantiuk, Tobias Ritschel, and Alessandro Artusi
- Reverse/Inverse Tone Mapping (~45 mins) :
 Francesco Banterle
- Image Spatial Resolution Retargeting (~45 mins) :
- Diego Gutierrez
 Temporal Image Retargeting (~70 mins) :
- Tobias Ritschel and Elmar Elsemann
 Image and Video Quality Assessment(~70 mins) :
- Tunç O. Aydın
- Stereo Content Retargeting (~50 mins):
 Piotr Didyk

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Ca	Urographics gliari, Italy ince of the European Associati	2012 May 13 - 18	TER GRAPHICS
	Tone Mapp	ing	
	Rafal Mantiuk		
BANGOR	Bangor University, UK		
9	Research Institute of Visual Corr	puting	
	http://www.bangor.ac.uk/m	nantiuk/	1

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Learning outcomes

What is tone-mapping?

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- What problem(s) does it solve?
- Why is the problem so difficult?
- How do we perceive high dynamic range images?
- What are the major approaches to tonemapping?
- How to choose a tone-mapping for a particular application?

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Tone Mapping?HDR ?Or something

else?



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What is tone-mapping?

Although tone-mapping may have different meanings, this course is about:

- A) Transformation of an image from an unrestricted color gamut of real world or an abstract scene to the restricted color gamut of a device
- B) Retargeting the perceptual appearance from one viewing conditions to another

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HDR (approximate) physical units luminance linear RGB Scene-referred LDR (SDR) bluma gamma corrected R'G'B' display referred

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Luminance

• Luminance – perceived brightness of light, adjusted for the sensitivity of the visual system to wavelengths $\int_{-\infty}^{\infty} I_{2} = \int_{-\infty}^{\infty} I_{2}(2) V(2) d2$

Light spectrum (radiance)	Luminous efficiency function (weighting)
4	
	1



Do HDR images contain luminance values?

- Not exactly, because:
 - the combination of camera red, green and blue spectral sensitivity curves will not match the luminous efficiency function
- But they contain a good-enough approximation for most applications
 - For multi-exposure camera capture the error in luminance measurements is 10-15%







Fechner law



- · Practical insight from the Fechner law:
- · The easiest way to adopt image Gustav Fechner [From Wikipedia] processing algorithms to HDR images is to convert luminance (radiance) values to the logarithmic domain



But...the Fechner law does not hold for the full luminance range

- · Because the Weber law does not hold either
- Threshold vs. intensity function:



Weber-law revisited

· If we allow detection threshold to vary with luminance according to the t.v.i. function:





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Major approaches to tone-mapping

- Illumination & reflectance separation
- Forward visual model
- Forward & inverse visual models
- Constraint mapping problem
- This is not a crisp categorization
 - Some operators combine several approaches

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Major approaches to tone-mapping

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Illumination and reflectance

Illumination

- Sun ≈ 10⁹ cd/m²
 White ≈ 90%
 Lowest perceivable
 luminance ≈ 10⁻⁶ cd/m²
- Dynamic range 10,000:1 Dynamic range < 100:1
- or more

Reflectance

- Visual system partially
 discounts illumination
 - Reflectance critical for object & shape detection

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Reflectance & Illumination TMO

- Distortions in reflectance are more apparent than the distortions in illumination.
- Tone mapping could preserve reflectance but compress illumination



for example:
$$I_{J} = R \cdot L^{1/j}$$

How to separate the two?

- (Incoming) illumination slowly changing
 except very abrupt transitions on shadow boundaries
- Reflectance low contrast and high frequency variations







WLS filter	
 Weighted-least-square 	s optimization
Make reconstructed image u possibly close to input g	Smooth out the image by making partial derivatives close to 0
$\sum_{p} \overline{\left(\left(u_{p}-g_{p}\right)^{2}+\lambda\left(a_{x,p}(g)\right)\left(\frac{\partial u_{p}}{\partial x}\right)\right)^{2}+\lambda\left(a_{x,p}(g)\right)\left(\frac{\partial u_{p}}{\partial x}\right)^{2}}$	$\left(\frac{u}{x}\right)_{p}^{2} + a_{y,p}(g)\left(\frac{\partial u}{\partial y}\right)_{p}^{2}\right) \rightarrow \min$
	Spatially varying smoothing – less smoothing near the edges

• [Farbman et al., SIGGRAPH 2008]



WLS filter

Stronger smoothing and still distinct edges





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Can produce stronger effects
 with fewer artifacts



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Retinex

- Retinex algorithm was initially intended to separate reflectance from illumination [Land 1964]
 - There are many variations of Retinex, but the general principle is to eliminate from an image small gradients, which are attributed to the illumination



<text><text><image><image><image>





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Tone mapping in photography

 Dodging and burning
 Darken on brighten image parts by occluding photographic paper during exposure
 Ansel Adams, The print, 1995

Photoshop tool



 Essentially – attenuate low-pass frequencies associated to illumination



Automatic dodging and burning

- Reinhard et al., Photographic tone reproduction for digital images. SIGGRAPH 2002
- Choose dodging an burning kernel size adaptively
- depending on the response of the center-surround filter

thus avoid halo artifacts



Major approaches to tone-mapping

Illumination & reflectance separation

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- Forward visual model
- Forward & inverse visual model
- Constraint mapping problem

Forward visual model

Mimic the processing in the human visual system
 Brightness,
 abstract response

	Lummanoc	,	0000000000	ponioo
Original image	radiance	Visual model	\Rightarrow	Displayed image
		· · · · · · · · · · · · · · · · · · ·		-

 Assumption: what is displayed is brightness or abstract response of the visual system

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Forward visual model: Retinex

- Remove illumination component from an image
 Because the visual system also discounts illuminant
- Display 'reflectance' image on the screen

Assumption:

- The abstract 'reflectance' contains most important visual information
- Illumination is a distraction for object recognition and scene understanding

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Sigmoidal tone-cu	rves
 Very common in digital cameras Mimic the response of analog film Analog film has been engineered for many years to produce optimum tone-reprodu must not change) 	2.0 5.15 1.0 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0
 Effectively the most c mapping! 	ommonly used tone-

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Why sigmoidal tone-curves work

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- Because they mimic photoreceptor response
 Unlikely, because photoreceptor response to steady light is not sigmoidal
- Because they preserve contrast in mid-tones, which usually contains skin color
- · We are very sensitive to variation in skin color
- Because an image on average has Gaussian distribution of log-luminance
- S-shape function is the result of histogram equalization of an image with a Gaussian-shape histogram

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Lightness perception

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- Lightness perception in tone-reproduction for high dynamic range images [Krawczyk et al. '05]
- Based on Gilchrist lightness perception theory



frameworks



Results - lightness perception TMO



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- Major approaches to tone-mapping
- Illumination & reflectance separation
- · Forward visual model
- Forward & inverse visual model
- Constraint mapping problem







	une appointation
 Multi-scale model of adaptation and spatial vision and color appearance (Pattanaik et al. '98] Combines psychophysical threshold and superthreshold visual models light & dark adaptation models Hunt's color appearance model One of the most sophisticated visual models 	



Forward and inverse visual model

Advantages of F&I visual models

- Can render images for different viewing conditions
 Different state of chromatic or luminance adaptation
 Physically plausible
- output in the units of luminance or radiance
 Shortcomings F&I visual models
- Assume that a standard display can reproduce the
- Assume that a stationard display can reproduce the impression of viewing much brighter or darker scenes
 Cannot ensure that the resulting image is within the
- dynamic range of the display
- Not necessary meant to reduce the dynamic rangeVisual models are difficult to invert

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visual models are difficult to

Major approaches to tone-mapping

- Illumination & reflectance separation
- · Forward visual model
- Forward & inverse visual model
- Constraint mapping problem

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Global tone mapping operator





Display limitations







Histogram equalization









Histogram adjustment with a linear ceiling

- Truncate the bins that exceed the ceiling
- Recompute the ceiling based on the truncated histogram





Display adaptive tone-mapping









Results: ambient illumination compensation



Results: ambient illumination compensation







Tone-mapping for video compression

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Which tone-mapping to choose?

- Illumination & reflectance separation
- · Forward visual model
- Forward & inverse visual model
- Constraint mapping problem

1. Think what is the target application - and thus the goal of your tone-mapping

2. Consider which tone-mapping approach(es) will deliver that goal

Future of tone-mapping

Tone-mapping of today Tone-mapping of tomorrow

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Built into cameras
Assumes that all

displays are the same



 Depending on viewing conditions, viewer, its capabilities
 Content recorded, stored and

 Display tone-maps content on demand

transmitted in an HDR format

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Apparent Contrast and Brightness Enhancement

Tobias Ritschel MPI Informatik

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Motivation

- Image display
 - Dynamic range of existing displays is limited
 - No reproduction real-world contrast/brightness
 - Good image appearance doesn't require that
- Modern tone mapping operators good at optimizing the physical contrast and luminance use

Motivation

- Human preference
 - Enhanced contrast and brightness improve image appearance
- Can we still boost the contrast and brightness impression?

Human perception • Spatial vision • Cornsweet illusion Apparent contrast boost • Glare illusion Apparent brightness boost

et al.

λ

Contrast Enhancement: Motivation

- Usual contrast enhancement techniques
 - either enhance everything
 - or require manual intervention change image appearance
- Tone mapping often gives
- numerically optimal solution • no dynamic range left for enhancement





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gradual darkening / brightening towards a contrasting edge
 contrast appears with 'economic' use of dynamic range

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Krawczyk et al. EG2007

Details of Contrast Illusion

ACTUAL SIGNAL	WHAT YOU SEE
-1-1-1-	

Krawczyk et al. EG2007

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Krawczyk et al. EG2007

Details of Contrast Illusion ACTUAL SIGNAL WHAT YOU SEE

- Luminance profiles cause contrast
- Properties:

-

- Shape matches shape of the enhanced feature
- Amplitude defines the perceived contrast
- Noise (texture) does not cancel the illusion
- Profiles should not be discernible







Construction of Simple Profile (2/2)



 Well preserved signal is exaggerated by unsharp masking Krawczyk et al. EG2007

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- Contrast for larger scales appears also on smaller scales
- the full profile is always reconstructed (red)
- Scale of contrast defines the profile size





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Adaptive Countershading















Purpose: Contrast Restoration









Colourfulness Countershading



promotes FG/BG separation

• creates impression of greater dynamic range

Smith et al. EG200

Smith et al. EG200

Smith et al. EG2006

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increases impression of depth





Color2Grey Application

 Isoluminant color pattern transformed to grey G using Helmholz-Kohlraush effect, which takes into account the contribution of chromatic component into brightness



Smith et al. EG2008

Smith et al. EG200



tors applied to a spectrum of isoluminant colours, compared to CIE L*.

Color2Grey Application



Color2Grey Application Original GIMP greyscale



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	Our G' p=0.75 k=[0.2,0.6,0.4,0.4]		
	Our G (p10.75 https://d.0.04.0.4)		

Countershading in 3D?

- Cornsweet in 3D is More plausible → Less of an artefact → Stronger → Better
- D. Purves, A. Shimpi, R. B. Lotto An empirical explanation of the Cornsweet effect. J. of Neuroscience 19, 1999



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Smith et al. EG2008

Scene-aligned Countershading



s. Dall, Landscape with Butter
Scene-aligned Countershading



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3D Unsharp Masking

• $U(S) = S + \lambda(S - S\sigma)$









2D vs. 3D Unsharp Masking Comparison

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	2D	3D
Signal	Image	Lit Surface
Smoothing	(Gaussian) Image Blur	Laplacian Surface Blur
Representation	Pixels	Lit vertices and pixels
Smoothness σ	Image distance	Geodesic world distance
Strength λ	Factor	Factor





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Results – Legibility



Normal Enhancement

- Only geometric term
- Shadows ?
- Hightlights ?
- Reflectance ?
- Vertex resolution
- 3D unsharp masking: Pixel resolution



Cignoni et al. '05, C & G Vol. 29

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Exaggerated Shading

- Object enhancement
 - Illuminate each vertex at grazing angle
 - Improves geometry understanding
 - Highlights?
 - · Shadows?

- Scene enhancement
 Change everything
- Both have applications Rusinkiewicz et al., SIGGRAPH'06

Specular shading



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Ihrke et al. SPIE2009

Study • Goals

- Find suitable settings
- See limitations
- Rank preference
- Method of adjustments
 - Strength λ : adjustable
 - + Fixed width $\sigma\!$ low, medium, high
 - 4 scenes, 15 participants
 - Task: Find such λ that:
 - Added enhancement is just noticeable
 - · Added enhancement becomes objectionable
 - Image appearance is preferred



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thrke et al. SPIE2009 Eurographics

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Countershading parameter effect



Unsharp masking, countershading and haloes: Enhancements or artifacts? M.Trentacoste, R. Mantiuk, W. Heidrich, F. Dufrot Eurographics 2012

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Applications: Image Resizing

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Applications: Viewer-adaptive display



Applications: Tone-mapping





Summary

- Better communicate image contents with a minimal change to image appearance
- Application of Cornsweet illusion to image enhancement
 - Generalization of unsharp masking
 - Automatic enhancement given the reference data:
 HDR image
 - depth information
 - shading in 3D scene
 - Scene consistent 3D unsharp masking leads to even stronger effects

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Glare Illusion [Zavagno and Caputo 2001]





Glare Illusion



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Eurographics 2012, Cagliari, Italy **Glare Illusion in Different Media**







 Simple
 approximation: convolution with Gaussian Already does a good job in conveying brightness Yoshida *et al*. (2008)

In Games

-



Kawase: Practical Implementation of High Dynamic Range Rendering. **Game Developer's Conference 2004**

Glare in Realistic Rendering

- Optics-based models for rendering glare
 illusion
 - [Nakamae et al. 1990]
 - [Ward Larson et al. 1997]
 - [Kakimoto et al. 2004, 2005]
- [Van den Berg et al. 2005]
- [Spencer et al. 1995]



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Dynamic Glare



- Realism
 - MovementColors
 - Required
 - Model of dynamic human eye to simulate temporal glare
 - Study Can temporal glare boost even further boost brightness?

Ritschel et al. EG2008





 $K = 1/(\lambda d)^2$ $E(x_{\rm p}, y_{\rm p}) = e^{i\frac{\pi}{\lambda d}(x_{\rm p}^2 + y_{\rm p}^2)}$

Single-plane

Ritschel et al. EG2008



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Aperture: Pupil

- Adaptation
- Can convert HDR image into pupil size

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Pupillary hippus











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Aperture: Vitreous Humor





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Aperture: Vitreous Humor

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Aperture: Eyelashes (optional)





Chromatic Blur

 Compute one wavelength - Get others for free!

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Convolutio	on		
HDR image	PSF	Bright pixels	Billboard
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L	٠	• 1 =	4
			Convolution
			Eurographics







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Billboard Eurographics **Temporal Glare Pipeline**





Psychophysical Experiment

- Goal: Measuring the brightness boosts caused by glare illusion
- 2 methods, 6 patterns for each
- Gaussian: blurring kernel Cheap approximation
- Spencer et al.: human eye's PSF (disability glare) Optical correctness

Yoshida et al. APGV2008

• 10 subjects20 minutes per person





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Perceptual Experiment



Task:

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Adjust the target disk luminance as close as possible to that of the Reference, but slightly yet visibly darker/brighter.

Yoshida et al. APGV2008

Method I (Gaussian)

Yoshida et al. APGV2008 Europraphics









Summary/Limitations

- Glare illusion might boost apparent brightness up to 30%
- Comprehensible model of light scattering in the eye taking into account dynamic eye elements
- Real-time rendering

-

- Other temporal low-level eye physics like
 Floaters
 - Local adaptation ("After images")

```
http://www.mpi-inf.mpg.de/resources/hdr/TemporalGlare/
```

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Acknowledgements

 I would like to thank Karol Myszkowski, Grzegorz Krawczyk, Kaleigh Smith, Akiko Yoshida, and Matthias Ihrke for help in preparing slides.

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Color Space



















Mantiuk et al.. "Color Correction for Tone Mapping", Proceedings Eurographics 2009.





Color in High Dynamic Range



































Gamut Mapping Aims (CS)

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Gamut Mapping Aims (CS)

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Gamut Mapping Aims (CS)

Limiting out of gamut colours

- Soft clipping can be afterwards adopted to eliminate these extremes
- Increase Image saturation
- Destination gamut has reduced saturation
- Helps maintaining the original chroma differences of the input Image







Gamut Mapping that preserves metric hue angle
 No Hue shift after compression or clipping

 CIELab is suffering of non linearity in blue regions, but also in red regions
Braun and Fairchild. "Color Gamut Mapping in Hue-Linearized CIELab Color Space"

Point-wise Gamut Mapping Techniques

Clipping

- It changes colours which are outside of the destination gamut,
- mapping them on the boundaries of the destination gamut - Horizontal (lines of constant lightness)
 - Radial to a centre of Gravity
 - Centre of lightness axis (Constant)Lightness corresponding to the Chroma Cusp (variable)
- Distance in CIELab
 - To the colour boundary of the destination gamut that has the smallest distance (HPMin ΔE Clipping)







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Preserve Saturation







Point-wise Gamut Mapping Techniques

Compression

It makes changes to all the colors of the source gamut to be

accommodated into the destination gamut .

- Linear

Sigmoid
 Knee-function

Parametric

The behaviour change based on the shapes of the two gamut's

(source and destination) at the hue angle, or it depends from user

parameters. (Clipping and Compression)











Preservation of Spatial Details

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Optimization

Making use of Human Visual System Models minimize the perceived differences between the input and output image.

Multiscale

- Re-inserts high-frequency information content in the gamut mapped image (clipped).
 - Clipping loss of details
 - General framework has been proposed that includes the different cases









Conclusions

- Works on high dynamic range imaging have mostly operated on luminance (lightness) information
 - some works start to appear proposing solution for color saturation, acquisition of colorimetric correct high dynamic range color values, and color appereance
- In Color Science a lot of works have been presented in the context of colorimetric characterisation, color appearance and gamut mapping on low dynamic range [0, 100]
 - Some of these works have been extended or re-used for high dynamic range applications
 - Tone mapping can bee seen as an extension or a particular case of gamut mapping (if we consider only the luminance information)
 - Many gamut mapping works started to analyse the details preservation on color information

Low Dynamic Range [0,100]

Acknowledgments

- Image IM2-Color (slide 2) Courtesy of Laszlo Neumann
- Material from the paper "Color Correction for Tone Mapping" Courtesy of Rafal Mantiuk
- Image Bottles (slides 12 and 15) Courtesy of
- Francesco Banterle
 Images (slides 18, 30 and 41) Courtesy of Ela Sikudova
- HDR Image s(skide 18) Martin Cadik





Inverse/Reverse Tone Mapping

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Outline of the Talk

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- An Overview on Reverse/Inverse Tone Mapping
- Expansion Methods:
- Global Methods
- Expand Map Methods
- Classification Methods
- User Based Methods
- Evaluation:

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- Psychophysical Experiments
- Computational Metrics
- Conclusions



Overview on RTM/ITM: Why?

 Why do we need RTM/ITM?
 We want to retarget LDR content into HDR monitors, applications (i.e. Image Based Lighting), and editing!

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- Case also

The general operator is typically defined as:



- Common steps of these operators:
- Linearization of the LDR imageNoise and quantization reduction
- Luminance Expansion

Global Methods (I)



Global Methods (II)





Global Methods (III)

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 Akyüz et al. [AFR*07] shown that "a simple linear scale can provide an HDR experience" based on psychophysically experiments:

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 $L_{\rm w}({\bf x}) = k \left(\frac{L_{\rm d}({\bf x}) - L_{\rm d, min}}{L_{\rm d, max} - L_{\rm d, min}} \right)^2$

 Masia et al. [MAF*09] shown that for over-exposed images a nonlinear function (gamma) needs to be applied. This non-linearity depends on exposedness of the image:

 $L_{\rm w}({\bf x}) = L_{\rm d}({\bf x})^{\gamma}$ $\gamma = 10.44k - 6.282$

 $k = \frac{\log L_{\rm d, \ avg} - \log L_{\rm d, \ Min}}{\log L_{\rm d, \ Max} - \log L_{\rm d, \ Min}} \quad k > 0.65$



Global Methods (IV)



-Custan





Classification Methods: Enhancement of Bright Videos (I)

- Didyk et al. [DMHS08] extended Meylan et al.'s method:
- Three classification areas: diffuse, reflections, and lights
- Automatic Classifier (AC):
 SVM + Nearest Neighbor + Tracking ⇒ 3% error
- User interface for adjusting the AC errors
- Non-linear adaptive tone curve for expanding the range based on the histogram of the region:
- Bilateral filtering layers separation (high and low frequencies) for avoiding contouring



Classification Methods:

Enhancement of Bright Videos (II)



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Classification Methods: Selective Reverse Tone Mapping (I)

- Masia et al. [MFSG10] proposed a novel approach based on saliency:
- Range Expansion (RE): pice-wise linear expansion using the zonal system by Adams (9 zones):

 $p = \left(\frac{\exp(v\sin(\pi\frac{z-1}{16})) - 1}{\exp(v) - 1}\right)^{\frac{1}{2},\frac{1}{2}} \qquad v = 5.25 \quad z \in [0,9]$

Labeling:

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salient objects and background discrimination using different techniques:

- learning-based saliency detection (Liu et al. [LSZ*07])
- saliency cuts (Fu et al. [FCLL08])

• Different Labels ⇒ Different RE functions



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Expand Maps Methods: Non-Linear Expansion using Expand Maps (I)

Banterle et al. [BLDC06, BLDBC07, BLDC08, B09] presented
 a general and real-time framework:

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- Range Expansion: non-linear (inverting an TMO; other functions)
- Expand Map: sampling+density estimation+cross bilateral (avoiding contouring and compression artifacts)



Expand Maps Methods: Non-Linear Expansion using Expand Maps (II)





= Climpatha

Expand Maps Methods: Non-Linear Expansion using Expand Maps (II)



IBL using original HDR IBL using expanded LDR

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Expand Maps Methods: LDR2HDR (I)

 Rempel et al. [RTS*07] presented a similar work of Banterle et al.:

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- Range Expansion: linear
- Expand Map: thresholding+filtering+edge stopping



Expand Maps Methods: LDR2HDR (II)



 A variant of the algorithm was presented by Kovaleski and Oliveria [KO09] using the bilateral grid to improve the quality of the Expand Map.

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User Based Methods: Hallucination (I)

- Wang et al. [WWZ*07] proposed the first user based method with reconstruction of details:
- HDR frequencies using the bilateral filter: base (low) and detail (high) layers
- Automatic Expansion (base layer): saturated regions are fitted using 2D Gaussian lobes (elliptical)
- Reconstruction (detail layer)
- Automatic: texture synthesis
 User-based: Stamp tool (similar to the Healing tool of Photoshop 7)
- NOTE: other images can be used as source for the missing details



User Based Methods: Hallucination (II)



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Mexican Mug's image is courtesy of Ahmet Oguz Akyuz

User Based Methods: Hallucination (III), Copying Fine Details in the Detail Layer



Evaluation: Why validation

- Need to evaluate different expansion methods against a "ground truth". Why?
- To understand weak features or drawbacks
- To understand important features
- rTMO/iTMO techniques do not generate exact luminance values
- Evaluation:
- Perceptual Image Metrics: not exact comparison as in the PSNR, RMSE, etc.
- Psychophysical Experiments

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Evaluation: Perceptual Image Metrics

- HDR-VDP (current version 2.1) [MDMS04,MKRH11]: determines the probability for each pixel of being different:
- Banterle et al. [BLDC06, BLDCB07, BLDC08, B09] used it to validate that their models were performing better than a simple non-linear expansion, validate against other methods, etc.

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- DI-IQA [AMMS08]: detects changes in details visibility, quantization artifacts. Validation of the quality in general:
- Masia et al. [MAF*09] and Kovaleski and Oliveria [KO09] used it to prove that their methods introduce less distortions during LDR expansion

Evaluation: Perceptual Image Metrics (II)



Lucy model is courtesy of the Stanford 3D Scanning Repository

Evaluation: Psychophysical Experiments

- Pairwise comparisons of HDR videos [DMHS08]:
 validation of the method against LDR, and LDR2HDR
- Pairwise comparisons of HDR images [BLD*09]: comparisons for image visualization and IBL:
- quantization artifacts need to be handle for better quality.IBL needs non-linear expansion.
- Rating of HDR images and tone mapped expanded images [MAF*09]:
 - understanding preferences in very over-exposed area
 - understanding artifacts in expanded images.

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Conclusions:

- LDR Expansion for HDR applications:
- LDR expansion methods are needed to be used in HDR applications (HDR visualization, Image Based Lighting, etc.)

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- The size of over/under-exposed areas is a limitation when recreating the content
- What's important?
- To have non-linearity or controllable expansion functions
- Avoid artifacts' boosting: quantization and JPEG-like
 compression
- Take care of over-exposed areas differently





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Common solutions

- Homogeneous squeezing/stretching
- Cropping [DeCarlo and Santella 2002; Viola and Jones 2004...]
- Hybrid solution [modern TV sets]





Eurographics

	Eurographics 2012, Cagliari, Italy	
Visual Media Retargetin	g: Siggraph Asia Course 2009	
Ariel Shamir	Olga Sorkine	
The Interdisciplinary Center, Herzlive	a New York Univeristy	
19 cr.54 🛞	Europraphics overweitigter and the	
	Eurographics 2012, Cagliari, Italy	
Visual Me	edia Retargeting: An Example	
	(Avidar & Shamir 2007)	
V ())		
	Eurographics 2012, Cagliari, Italy	
Visu	al Media Retargeting: Scaling	
	and the second sec	
A CALLER AND	Scaling	
	[Avidar & Shamir 2007]	
Proved (A)		

	Eurographics 2012, Cagitari, Italy
V	isual Media Retargeting: Seams
	Insert & remove seams
	scang
	[Avidar & Shamir 2007]

Eurographics 2012, Cagiari, Italy Visual Media Retargeting: Energy Concept





[Avidar & Shamir 2007]

Eurographics 2012, Cagliari, Italy

Eurographics

Visual Media Retargeting: Energy & Saliency

- Magnitude of gradients (simple)
- Saliency (e.g. Itty's method) multi-res





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Different energy functions

Eurographics 2012, Cagliari, Italy





Eurographics 2012: Cagliari, Italy Different energy functions



10 cr.54 Eurographics



Simple operators: cropping

- Crop s.t. important (salient) parts remain
- Use domain-specific tools, such as face detector, gaze estimation... [DeCarlo and Santella 2002; Viola and Jones 2004]



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Simple operators: scaling

Eurographics 2012, Cagliari, Italy

Eurographics

Eurographics

- Can combine with cropping techniques (done on modern TV sets – center remains, peripheral data is scaled)
- Distorts content but is perfectly temporally coherent (video)





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Eurographics 2012, Cagliari, Italy
Discrete vs continuous
Figure 2: A digital image as a 2D discrete grid of pixels. In this case the cells contain 3 values of RGB color.
•

Figure 3: A digital image as a sampling of a continuous function.

Eurographics 2012, Cagli

Problem statement

Eurographics

- Given an image I of size (n x m), we want to produce an image I* of size (n* x m*) which is a good representative of image I
- But what is a "good representative"? No definitions exist
- Goals of a retargeting algorithm:

VCR54 🚳

- 1. The important content of I should be preserved in I*.
- 2. The important *structure* of I should be preserved in I*.
- 3. I* should be artifact-free



Eurographics 2012, Cagliari, Italy Discrete approaches

- Seam carving for content aware image resizing
 SIGGRAPH 2007
 S. Avidan and A. Shamir
 Improved seam carving for video retargeting
 SIGGRAPH 2008
 M. Rubinstein, A. Shamir and S. Avidan
 Seam carving for Media Retargeting
 Trans. Of the ACM
- S. Avidan and A. Shamir
- Multi-Operator Media Retargeting
 - SIGGRAPH 2009
- M. Rubinstein, A. Shamir and S. Avidan
- ...and the list goes on

	Continuous approaches
Featu	ure-aware texturing
• 1	EGSR 2006
• 1	R. Gal, O. Sorkine and D. Cohen-Or
Non-	homogeneous content-drive video retargeting
• 1	CCV 2007
• 1	L. Wolf, M Guttmann and D. Cohen-Or
Optir	mized scale-and-stretch for image resizing
• 9	SIGGRAPH ASIA 2008
• 1	Y. Wang, C. Tai, O. Sorkine and T. Lee
Shrin	kability maps for content-aware video resizing
• 1	Pacific Graphics 2008
• 1	Y. Zhang, S. Hu and R. Martin
and	the list goes on

Eurographics 2012, Cagitari, Itary Discrete example: Seam carving



[Rubinstein, Avidan and Shamir 2007]

> Eurographics 2012, Cagilari, Italy Seam carving



[Rubinstein, Avidan and Shamir 2007]

Eurographics



Eurographics 2012, Cagliari, Italy Seam carving

[Rubinstein, Avidan and Shamir 2007]

Eurographics 2012, Cagliari, Italy

Eurographics

Eurographics

P-----4 🛞



Continuous example: Warping

- Allow important regions to uniformly scale
- Find **optimal** local scaling factors by global optimization
- Result: preserve the **shape** of important regions, distort non-important ones



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Continuous example: Warping

Eurographics

Eurographics

Eurographics

 Grid mesh, preserve the shape of the important quads



 Optimize the location of mesh vertices, interpolate image

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Continuous example: Warping





Eurographics 2012, Captierr, Italy Video?	
Naïve every frame by itself	
Improved seam carving for video resizing [SIGGRAPH 2008]	
Eurographics 2012, Caglian, Italy	
The	
Contraction	
Gurogaphics 2012. Copilari. Haly	

_

Slightly less naïve...

Eurographics 2012, Cagliari, Italy

Reduction of the video problem to image seam carving by using projection of maximum energy through time:



Reduction of the video problem to image seam carving by using projection of maximum energy through time:







	Eurographics



Eurographics 2012, Cagliari, Italy



Eurographics 2012, Cagliari, Italy

Problems?

More complex scenes:

- Object movement
- Camera movement



Eurographics 2012, Cagliari, Italy

More Complex Scenes

- More complex scenes:
 - Object movement Camera movement
 - Camera moveme



More Complex Scenes

P-----4 🛞

Seams should adapt and change through time!

Eurographics 2012, Cagliari, Italy

Eurographics



Eurographics 2012, Cagitan, Itay



Eurographics 2012: Cagitori, Italy











Eur





Current State of Retargeting Research





Eurographics

Eurographics

Relation between the operator and the type of content?

Computational retargeting measure?

A Comparative Study of Image Retargeting Miki Rubinstein, Diego Gutierrez, Olga Sorkine and Arik Shamir ACM Transactions on Graphics, Vol. 29(5) (SIGGRAPH Asia 2010)

Benchmark and evaluation methodology for image retargeting

RetargetMe

http://people.csail.mit.edu/mrub/retargetme/

 Comprehensive perceptual study and analysis of image retargeting

Eurographic	s 2012, Cagliari, Italy
	Goals
• What is the "correct" way to retarget this image?	
	s 2012, Cagliari, Italy

Goals

Eurographics

- The dataset and user study
- User response (subjective) analysis
 Is there consensus between viewers?
- When is one method better than another?
- Computational (objective) analysis
 - Can an image distance measure predict retargeting quality?

Kobinstein, Guberre

Constructing the Dataset

Eurographics 2012, Cagliari, Italy

- Image Retargeting objectives:
- 1. Preserve the important *content* and *structures*
- 2. Limit artifacts



Retargeting Operators

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Seam Carving [SC]	[Rubinstein et al. 2008]	Ū
Shift Map [SM]	[Pritch et al. 2009]	iscre
• Multi-Operator [MULTIOP]	[Rubinstein et al. 2009]	ĕ
Warping [WARP]	[Wolf et al. 2007]	C on
Streaming Video [SV]	[Krähenbühl et al. 2009]	tinu
 Scale-and-Stretch [SNS] 	[Wang et al. 2008]	S
Cropping [CR]	[Manual]	Ref
Scaling [SCL]	[Cubic interpolation]	əren
		8

Eurographics 2012, Cagliari, Italy

Eurographics

Eurographics 2012, Cagliari, Italy

Comparative Analysis







Eurographics 2012, Cagliari, Italy

User Statistics

- Each participant performs 12 comparisons over 5
 images
- 210 participants; 252 votes per image
 - Halfamazonmechanical turk
 - Half (25 cents per completed survey)
- Average time to complete: 20 minutes
 "It was a very interesting survey. Very nice experience"
 - "i need your more survey so that i can help u a lot"





Eurographics 2012, Cagliari, Italy	
User Agreement	
-	
 Similarity of votes = consensus on "good" retargeting 	
Coefficient of Agreement [Kendall 1940]	
 a_{ij} = # times method i chosen over method j 	
 m = # participants 	
 t = 8 (# retargeting operators) 	
•	
Rubinstein, Gutierrer, Sorking and Shamin 2010	

Eurographics 2012, Cagliari, Italy

User Agreement

	lines/	faces/	Textur	foregroun	Geometri	Symmetr	Total
	edges	people	e	d	с	у	
				objects	Structure		
					S		
u	0.073	0.166	0.070	0.146	0.084	0.132	0.095

Low agreement in general

• Greater agreement on images containing faces/people, evident foreground objects and symmetry.

	Rubinstein, Gutierrez, Sorking and Shamir 2010
V 🛞	













Partial Conclusion

- (At least for our retargeted setup)
- SUBJECTIVE:
- Clear and consistent division in groups
- CR, SV, MULTIOP: good!
- SCL, SC, WARP: not so good
- Greater agreement for faces/people and foreground objects:

Saliency at object level?





Eurographics 2012, Cagliani, Italy Source is Usually Unknown!



Eurographics 2012, Cagliari, Italy

"No Reference" Experiment Results

Eurographics

- Similar setup, source image not shown
- New set of 210 participants



Eurographics 2012, Cagitari, Italy "No Reference" Experiment Results

1600		Re	ference	160		No Refere	nce
1200				12	10		
1000 -				100		▐╂╻╻╷	
800				8			
400				41			
200				21			
SV	C	R M		SM SI	NS S	CL WARP	SC
Streamii Video	ng Crop	oping o	Multi- perator	Shift- Sca maps Stre	le & Sca etch	ling Nonhomo Warping	o. Seam Carving
lines/ edges	faces/ people	texture	foreground objects	geometric structures	symmetry	Aggregate	Rank product
0.964	0.988	0.946	0.737	0.950	0.957	0.978	0.985

					Ор	erate	or Rankin
lines/edges			_	-			
CR M	ULTIOP	, sv	(SM	(SNS)	WARP	SCL	SC
faces/peop	le						
CR M	ULTIOP	SV)	(SM)	SCL	SNS	WARP	SC
texture							
MULTIC	P SV	CR	SM	SNS	WARP	SCL	SC
foreground	objects						
CR S	V MU	LTIOP	(SM)	SNS	WARP	SCL	SC
geometric :	structures		\sim				
CR M	ULTIOP	SV)	(SM)	SNS	SCL	WARP	SC
symmetry				_			
MULTIC	P SV	CR	SCL	SC	SM	SNS W	ARP

Computational Retargeting Measures

Eurographics 2012, Cagliari, Italy

Eurographics

 Goal: can computational image distance measures predict human retargeting preferences?

Can be used to evaluate new operators

 Can be used to develop new operators – [Simakov et al. 2008], [Rubinstein et al. 2009]

Rubinstein, Gutierrez, Sorkine and Sampra 200

(Non-blind) Retargeting Measures

Eurographics 2012, Cagliari, Italy



NCR54			Eurographics

Objective Measures

Eurographics

· High level semantics:

- Bidirectional Similarity [BDS] Simakov et al. 2008
- Bidirectional Warping [BDW] Rubinstein et al. 2009
- SIFT Flow [SIFTflow] Liu et al. 2008
- Earth Mover's Distance [EMD] Pele and Werman 2009
- · Low level features
- Edge Histogram [EH] Menjunath et al. 2001
 Color Layout [CL] Kasutani and Yamada 2001
- · See dataset website and supplemental material for more details

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How to Evaluate an Objective Measure?





Eurographics 2012, Cagliari, Italy **Objective Analysis Results**

Eurographics

Metric	lines/ edges	faces/ people	texture	Foreground objects	geometric structures	symmetry	total
BDS	0.04	0.19	0.06	0.17	0.00	-0.01	0.08
BDW	0.03	0.05	-0.05	0.06	0.00	0.12	0.05
EH	0.04	-0.08	-0.06	-0.08	0.10	0.30	0.00
a	-0.02	-0.18	-0.07	-0.18	-0.01	0.21	-0.07
SIFTflow	0.10	0.25	0.12	0.22	0.08	0.07	0.14
EMD	0.22	0.26	0.11	0.23	0.24	0.50	0.25

The results were spectacular(ly poor!)

- · We tried something else:
- SIFT-flow [Liu et al. 2008]: SIFT
- Earth mover's distance [Pele & Werman 2009]: EMD Somewhat better [©]

Can computational image distance metrics predict human retargeting perception?

Metric				Altribute						
	Line vEdges	Faces/People	Texture	Foreground Objects	Geometric Structures	Symmetry	Mean	std	p-value	
BDS	0.040	0.190	(1.060	0.167	-0.004	-0.012	0.083	0.268	0.017	
BDW	0.031	0.048	-0.048	0.060	0:004	0.119	0.046	0.181	0.869	
EH	0.043	-0.076	-0.060	-0.079	0.103	0.298	0.004	0.334	0.641	
CL	-0.023	-0.181	-0.071	-0.183	-0.009	0.214	-0.068	0.301	0.384	
RAND	-0.046	-0.014	0.048	-0.032	-0.040	0.143	-0.031	0.284	0.693	
CHITCHASE	0.097	0.252	0.119	0.218	0.085	0.071	0.145	0.262	0.031	
EMD	0.220	0.262	0.107	0.226	0.237	0.500	0.251	0.272	16.5	
EMD	0.220	0.262	0.107	0.226 a) Complete rank correl	0.237 ation (k = ∞)	0,500	0.251	0.272	le-5	
EMD Metric	0.220	0.262	0.107	0.226 (a) Complete rank correl Altribute	0.237 ation (k = ∞)	0.500	0.251	0.272 Total	le-5	
EMD Metric	0.220 Line vEdges	0.262 Faces/People	0.107	0.226 (a) Complete mail: correl Attribute Foreground Objects	0.237 ation (k = ∞) Geometric Structures	0,500 Symmetry	0.251 Mean	0.272 Total std	le-5	
EMD Metric BDS	0.220 Line vEdges 0.062	0.262 Faces/People 0.280	0.107 Texture 0.134	0.226 (a) Complete mark correl Alterbute Foreground Objects 0.249	0.237 ation (k = ∞) Geometric Structures -0.025	0.500 Symmetry -0.247	0.251 Mean 0.108	0.272 Total std 0.532	1e-5	
EMD Metric BDS BDW	0.220 Line vEdges 0.062 0.213	0.262 Faces/People 0.280 0.141	0.107 Texture 0.134 0.123	8,226 (a) Complete naik correl Altribute Foreground Objects 0,249 0,115	0.237 ation (k = 50) Geometric Structures -0.025 0.212	0.500 Symmetry -0.247 0.439	0.251 Mean 0.108 0.200	0.272 Total std 0.532 0.395	p-value 0.005 0.002	
BDS BDW EH	0.220 LinevEdges 0.062 0.213 -0.036	0.262 Faces/People 0.280 0.141 -0.207	0.107 Texture 0.134 0.123 -0.331	0.226 a) Complete mark correl Attribute Foreground Objects 0.249 0.115 -0.177	0.237 nion (k = 50) Geometric Structures -0.025 0.212 0.111	0.500 Symmetry -0.247 0.439 0.294	0.251 Mean 0.108 0.200 -0.071	0.272 Total std 0.532 0.395 0.593	p-valu 0.005 0.002 0.013	
BDS BDW EH CL	0.220 Line vEdges 0.062 0.213 -0.036 -0.307	0.262 Faces/People 0.280 0.141 -0.297 -0.336	0.107 Texture 0.134 0.123 -0.331 -0.433	0.226 a) Complete nank correl Foreground Objects 0.349 0.115 -0.177 -0.519	0.237 alion (k = ∞) Geometric Structures -0.025 0.212 0.111 -0.366	8,500 Symmetry -0.247 0.439 0.294 0.088	0.251 Mean 0.108 0.200 -0.071 -0.320	0.272 Total 9.532 0.395 0.593 0.543	p-value 0.005 0.002 0.013 1e-6	
BDS BDW EH CL SIFTbw	0.220 LinevEdges 0.062 0.213 -0.036 -0.307 0.241	0.262 Faces/People 0.290 0.141 -0.247 -0.336 0.428	0.107 Texture 0.134 0.123 -0.331 -0.433 0.312	0.226 a) Complete nank correl Attribute Foreground Objects 0.149 0.115 -0.177 -0.519 0.442	0.237 aton (k = ∞) Geometric Structures -0.025 0.212 0.111 -0.366 0.303	0.500 Symmetry -0.247 0.294 0.098 0.002	0.251 Mean 0.108 0.200 -0.071 -0.320 0.298	0.272 Total 9.532 0.593 0.593 0.543 0.483	p-value 0.005 0.002 0.013 1e-6 1e-6	

Table 6: Correlation of objective and addressive measures for the complete sound (tap) and for the dates highest models are the formation (bottom) is order observed time are correlation conference in a down of the 's _11, colorable at order all langes or its datases with the common ling attribute. The last three columns above the mean score, standard deviation, and respective p-value over all image types. Highest score in each column appears in bold.

	(Rubinstein, Gutierrez, Sorkine and Shamir 2010)
D	Eurographics

Conclusions

- SUBJECTIVE:
- More recent algorithms **do** outperform their predecessors in a (surprisingly) consistent way
- Cropping is the simplest and one of the best:
 loss of info OK

 - distortion NOT OK
 - bring it back!
- Interestingly, scaling and seam carving do not do very well on their own... but are two of the three in MULTIOP: combination of simple methods?

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Conclusions

Eurographics

Original	Build Seam Carving	(3) Cropping
		3

Conclusions

OBJECTIVE:

- We are a long way from predicting human perception
- Four similarity image metrics did not perform well at all
 Two metrics not originally designed for that purpose did somewhat better
- Optimize retargeting wrt those?
- Further research is (badly!) needed

Eurographics



 $\begin{array}{l} ColSim(C_{ori}^{0}, C_{ret}^{0}) = w_L SalSim(L_{ori}^{*0}, L_{ret}^{*0}) + \\ w_a SalSim(a_{ori}^{*0}, a_{ret}^{*0}) + w_b SalSim(b_{ori}^{*0}, b_{ret}^{*0}) \end{array}$

DCR34 🛞

Conclusions

Eurographics

Eurographics

We need video analysis and experiments!

V-----

Eurographics 2012, Caglari, Liaty Using Eye-Tracking to Assess Different Inage Retargeting Methods Sugao Cartillo Tilko kuid an Diang Gritierez	
Applied Perception in Graphics and Visualization 2011	
Using Eye-Tracking to Assess Different Image Retargeting Methods	-
Original Image MOP	
SM SV	
Eurographics 2012, Caylini, His y Using Eye-Tracking to Assess Different Image Retargeting Methods	
Susana Castillo,Tilke Judd and Diego Gutierrez Applied Perception in Graphics and Visualization 2011	
How to measure the relevance of a retargeting approach?	
now to measure the relevance of a retaigeting approach.	
(Chamaret et al. 2010)	
Eurographics 2012, Cagliari, Italy	
Overview	
[Castillo, Judd and Gutierrez 2011]	

	Eurographics 2012, Cagliari, Italy
R	etargeting Operators
Seam Carving [SC]	[Rubinstein et al. 2008]
Shift Maps [SM]	[Pritch et al. 2009]
Multi-Operator [MULTIOP] Streaming Video [SV]	[Rubinstein et al. 2009] [Krähenbühl et al. 2009]
Aggregate SV CR MULTIOP 1 2 3 Rank [Rubinstein et a	SNS (SCL WARP SC 5 6 7 8 II. SIGAsia 2010] (Castillo, Juid and Guiterrez 2011] Castellio, Juid and Guiterrez 2011]







Eye tracking data


Eurographics 2012, Cagliari, Italy
Eye tracking data
Learning to predict where humans look [Judd et al. 2009]
• • •
Average fixation locations / continuous saliency map
[Castilio, Judd and Gutierrez 2011]

ious saliency map
[Castillo, Judd and Gutierrez 2011]
Eurographics
Eurographics 2012, Cagliari, Italy
Ever tread is a data
Eye tracking data
k [Judd et al. 2009]



Learning to predict where humans look [Judd et al. 2009]

Eurographics 2012, Cagliari, Italy Eye tracking data

Original Image Horizon Horiz

	[Castillo, Judd and Gutierrez 2011]
V CR54	Eurographics Transmission and the second

Excernel 2012 Charlent, 1849 Eye tracking data	
(Castilio, Judd and Gutterrez 2011)	

Eurographics 2012, Cagliant, Italy MIT Predictive Model of Saliency







Examples and Discussion
[Castillo, Judd and Gutierrez 2011]
Eurographics

carographics zorz, cagita

Conclusions

- Lots of methods in the past few years, in top-notch places
- Relatively small impact in industry

RetargetMe

http://people.csail.mit.edu/mrub/retargetme/ or Google: "retargetme"

- We need more (and better!) metrics
- Does video retargeting really work?

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Eurographics

Eurographics

Conclusions

Eye-tracking data framework

- The model of saliency from Judd et al. [2009] can be an useful tool in a retargeting context when using an eye tracker is not feasible
- Analysis of 4 retargeting operators with 6 image distance measures

 Using eye-tracking data can improve the predicting capabilities of these measures
- Alteration of the image semantics.
 Content removal alters Rols although the results can be aesthetically pleasing
- Attentional tension between Rols and artifacts

 Large artifacts can remain unnoticed when not in a Rol (At least for our 5 second task)

Spatial Retargeting Diego Gutierrez Universidad de Zaragoza	
(slides material also from Miki Rubinstein, Olga Sorkine, Arik Shamir, Shai Avidan and Susana Castillo)	







Eurographics 2012, Capitar, Italy Second Observation • Many pixel computations are similar over space and time

Third Observation

Frames do not differ much...



Eurographics 2012, Cagliari, Italy

Eurographics 2012, Cagliari, Italy

Consequence

- Given:
- Pixel color determination is expensive
- Computations can be spread over space and time
- Frames are similar
- Reuse pixel information over space and time to reduce shading costs

Excretion 2012, Caluri, Italy Remember? • Observation: shading correlates with geometry • World information behind pixel is for "free" • Depth (position) • Normals • Normals • Geometric motion flow

Ungraded 2012. Colduri, Haiv Why does rendering of depth, motion & co. help? • Find correspondences and transfer shading!







































Euroranic 2012. Collicit. Ide Remember? • Observation: shading correlates with geometry • World information behind pixel is for "free" • Depth (position) • Normals • Geometric motion flow • Geometric motion flow







- Spatio-Temporal Upsampling
- Choose preferable method:
- *combine spatial upsampling* & *temporal caching*

Gain information over time?

• Over time, the same low-res image gives... the same information!





Eurographics 2012, Cagliari, Italy







Spatio-Temporal Upsampling [Herzog et al. 2010]

- Beneficial to use Spatial
 - & temporal upsampling
- Static frame convergence
- Robustness with respect to changing lighting conditions





















Extension to Stereo [Didyk et al. VMV'10]

- Adaptive Image-space Stereo View Synthesis
 More sophisticated (adaptive) warping











Warping

Very efficient Maps very well to GPU

Maps very well to GPU
 Executes in less than 4ms on a full-HD frame
 NVIDIA GT 460

- Easy to implement
- Important for streaming architectures

Conclusion

Spatio-temporal upsampling is very powerful

Eurographics 2012, Cegliari, Italy

- Extrapolation is possible
- Cheap alternatives to rendering all frames

Eurographics 2012, Cagliari, Italy

Eurographics 2012, Cagliari, Italy

So far...

- Different ways rendering (reconstruction, warping, etc.) allow us to produce more efficient high-quality imagery
- So far:
- Have a low computational cost to produce highquality
- Now:
- Make use of temporal domain to improve quality















Eirographics 2012, Capitari, Taly

- Fight mach banding artifacts
- Manually:
 Switch last color bit
- Useful for HDR imagery, but very high refresh rates needed...
- Based on perception (eye integration)



















	Eurographics 2012, Cagliari,
Many High-Resolut Photographs: > 10MPix	Panoramas: > 50MPix
Circupinal Photography	Computer generated: Unlimited
Gigapites Holography.	
A REAL PROPERTY OF THE PARTY OF	

















































Eurographics 2012, Cagliari, Italy

Conclusions Human perception is a crucial component to high-quality imagery Resolution & Colors physical screen capabilities Works for large range of commonly used display devices

Euroraphis2012 Colum. Hate Future? Bigger, better, faster... More realism More details More effects Higher quality beyond physical limitations Only first steps in this direction More to come...

Thank you very much for your attention!

Karol Myszkowski karol@mpi-inf.mpg.de

Elmar Eisemann e eisemann@telecom-paristech.fr

Eurographics 2012, Cagliari, Italy

Acknowledgments: Thank you for support in creating the slides go to Daniel Scherzer, Robert Herzog and Dawid Pajak



Stereo content retargeting

Piotr Didyk MPI Informatik

Why stereo?

Images are no longer flat

- Improves realism
- Images are not longer flat
- Better layout separation

Reproduced view dependent effects

Improves material perception

History of stereo

1838: different images for both eyes 1890: patent on 3D movies 1900: tripod for taking 3D pictures 1915: exhibition of 3D images 1922: 3D movie 1923: 3D movie with stereo sound 1952: 3D movie in color 90%: IMAX cinemas, TV series 2003: feature Tim in 3D for IMAX

2003: feature film in 3D for IMAX 2009 - now: became very popular



Number of 3D productions





Early 3D production

- Expensive hardware
- Lack of standardized format
- Impossible at home
- Lack of interesting content



Eurographics 2012, Cagliari, Italy

Eurographics 2012, Cagliari, Italy

Eurographics 2012, Cagliari, Italy

Number of 3D productions



Stereo in daily life



Eurographics 2012, Cagliari, Italy

Current 3D production

Great content:

Beautiful shots with complex depth
 Computer generated special effects

3D is coming to our homes:

- Equipment is getting less expensive
 3D games / TV

New better 3D equipment:

- Shutter glasses
 Polarized glasses
 Autostereoscopic displays are getting better They are flat!

Eurographics 2012, Cagliari, Italy

Stereo on a flat display



	Eurographics 2012, Cagliari, Italy	
Depth perception		
We see depth due to depth cues. Stereoscopic depth cues: binocular disparity		

Depth perception

We see depth due to depth cues.

binocular disparity Ocular depth cues: accommodation,



Eurographics 2012, Cagliari, Italy

Eurographics 2012, Cagliari, Italy

Depth perception


We see depth due to depth cues. Stereoscopic depth cues: binocular disparity Ocular depth cues: accommodation, vergence

Depth perception

We see depth due to depth cues.

Stereoscopic depth cues: binocular disparity Ocular depth cues: accommodation, vergence



Pictorial depth cues: occlusion,

Depth perception

We see depth due to depth cues.

Stereoscopic depth cues: binocular disparity

Ocular depth cues: accommodation, vergence





Eurographics 2012, Cagliari, Italy

Depth perception

We see depth due to depth cues.

Stereoscopic depth cues: binocular disparity Ocular depth cues:

accommodation, vergence
Pictorial depth cues:
occlusion, size, shadows...



Eurographics 2012, Cagliari, Italy

Cues sensitivity



Eurographics 2012, Cagliari, Italy

Depth perception

We see depth due to depth cues.

Stereoscopic depth cues: binocular disparity

Ocular depth cues: accommodation, vergence

Pictorial depth cues: occlusion, size, shadows... Challenge: Consistency is required!



Disparity & occlusion conflict



Disparity & occlusion conflict



 \Rightarrow

Depth perception

We see depth due to depth cues.

Stereoscopic depth cues: binocular disparity Ocular depth cues: accommodation, vergence

Require 3D space We cheat our Human Visual System!

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Eurographics 2012, Cagliari, Italy

Pictorial depth cues: occlusion, size, shadows...

Reproducible on a flat displays

Cheating our HVS



Viewing discomfort



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Comfort zones



<section-header>Decomposed 2012 Cognitient, 12dr Common common science Presented comment Presented co

"Controlling Perceived Depth in Stereoscopic Images" by Jones et al. 2001



Comfort zones



Presented contentViewing condition

Difficult scene, user allowed to look away from screen

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Comfort zones



"The zone of comfort: Predicting visual discomfort with stereo displays" by Shibata et al. 2011

Eurographics 2012, Cagliari, Italy **Depth manipulation** \bigcirc \bigcirc \bigcirc Viewing discomfort Eurographics 2012, Cagliari, Italy **Depth manipulation** Viewing discomfort Scene manipulation, Viewing comfort

Eurographics 2012, Cagliari, Italy

Camera manipulations



"Controlling Perceived Depth in Stereoscopic Images" by Jones et al. 2001





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Camera manipulations

Camera/Scene space



The parameters can be the same
 may cause discomfort

Different parameters for capturing the scene

"Controlling Perceived Depth in Stereoscopic Images" by Jones et al. 2001

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Camera manipulations



- Calculate appropriate camera parameters
- Adjustment in each frame

"Controlling Perceived Depth in Stereoscopic Images" by Jones et al. 2001 "Evaluating methods for controlling depth perception in stereoscopic cinematography" by Sun et al. 2009

Camera manipulations



Adjustment in each frame

"Controlling Perceived Depth in Stereoscopic Images" by Jones et al. 2001 "Evaluating methods for controlling depth perception in stereoscopic cinematography" by Sun et al. 2009

Camera manipulations

General procedure:

Define viewing condition
 Adjust cameras parameters
 Capturing

Displaying on different device: (captured content)

Potential discomfort
Recapturing ?



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Pixel disparity



Left + right view

Stereo content



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Eurographes 2012. Cogilian, 1839 Sources of pixel disparity

Stereo image pair Discussion Rendering Usually available

 Rendering
 →
 Usually available

 Only image pair
 →
 Computer vision technique

Disparity manipulations



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Stereoscopy from Light Fields

Stereoscopy from Light Fields





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"Multi-Perspective Stereoscopy from Light Fields" by Kim et al. 2011





2010	





"Nonlinear Disparity Mapping for Stereoscopic 3D" by Lang et al. 2010



Eurographics 2012. Claylium, 114 y



Disperception P cepture object (and the second se

Eyes position and interoccular distance changed

sensor

iense

"Image Distortions in Stereoscopic Video Systems" by Woods et al. 1993





Misperception



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Eurographics 2012, Cagitari, Italy Misperception Viewing distance = 1 m



Misperception

Head Rolt Closer Surface of Cube	В	09	lique V	aspo	int Cioser	Sutice	of Cube		•	Conve	nging (aners	e: Cło	er Su	1949 1	rcu
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-30	-20	-				83	100		-20	2	2					
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"Misperceptions in Stereoscopic Displays: A Vision Science Perspective" by Held et al. 2008

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Eurographics 2012, Cagliari, Italy 3D image prediction



Depth perception





"A perceptual model for disparity" by Didyk et al. 2011





One just-noticeable difference



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Eurographics 2012, Cagliari, Italy



How big is the detection threshold?





"Sensitivity to horizontal and vertical corrugations defined by binocular disparity." by Bradshaw et al. 1999

Eurographics 2012, Cagliari, Italy **Disparity perception** How significant is the difference?



Eurographics 2012, Cagliari, Italy

Discrimination threshold



Eurographics 2012, Cagliari, Italy

Disparity perception

Sensitivity to depth changes depends on:

- Spatial frequency of disparity corrugation
- Existing disparity (sinusoid amplitude)

<complex-block>

• The smoothed comparison • Weak have needed to define the second secon

Hinghtude eductioner[PEST with 2AFC]
 Thresholds measurement:
 12 participants → 300% samples



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"A perceptual model for disparity" by Didyk et al. 2011

Eurographics 2012. Chyliani. Itay Model







Eurographics 2012. Clagitari, Italy
The HVS response



The HVS response



Eurographics 2012, Cagliari, Italy

The HVS response



"A transducer function for threshold and suprathreshold human vision" by Wilson 1980 "A perceptual framework for contrast processing of high dynamic range images" by Mantiuk et al. 2005

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Perceptual space

We show so far:

(disparity, frequency) [arcmin, cpd]

HVS response [JND]

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Perceptual space



3D scene with pixel disparity [pixels] Map of HVS response [JND]

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Pixel disparity to disparity





Luminance (contrast perception)



Perceptual space (Perceived contrast)

Luminance

Luminance (contrast perception)



Contrast decomposed into frequency bands

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Eurographics 2012, Cagliari, Italy

Luminance (contrast perception)



Luminance (contrast perception)

Luminance ↔ Vergence	
Luminance contrast ↔ Disparit Disparity / Lur	y minance similarity:
Lowpass Inters	into frequency bands





Differences

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Vergence to disparity



Lowpass filters Differences

- · We can process frequencies independently
- Vergence → Disparity

Perceptual	model	



"A perceptual	model for	disparity"	by Didyk	et al. 2011

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Eurographics 2012, Cagliari, Italy



Disparity metric

For Luminance: "A visual discrimination model for imaging system design and development" by Lubin 1995

Disparity metric



"A perceptual model for disparity" by Didyk et al. 2011

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Eurographics 2012. Cligitian, 118 y Disparity manipulations

→ The HVS is taken into account → Efficient disparity reduction Mampulations in precontral space:



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Disparity manipulation



<section-header><figure><figure>

Eurographics 2012. Cagiliari, Itay



Eurographics 2012, Cagliari, Ita

Inverse model



Disparity manipulation



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Disparity manipulation





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Personalization

Disparity perception depends on:





Equipment

	Eurographics 2012, Cagliari, Italy
Personalization	
error and ensure the first state of the first state	Perceptual space
	"A perceptual model for disparity" by Didyk et al. 2011

Sare		
Band n		
Space		
ptual space		
or disparity" by Didyk et al. 2011		

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All users perceive the same regardless: • Equipment • Disparity sensitivity

Eurographics 2012, Cagliari, Italy

Backward-compatible stereo





Eurographes 2012. Coglian, 163 y









"A Craik-O'Brien-Cornsweet illusion for visual depth " by Anstis et al. 1997

Backward-compatible stereo



backward-compatible so

3D impression preserved
No artifacts when special equipment is unavailable

"A perceptual model for disparity" by Didyk et al. 2011

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Backward-compatible stereo



3D impression preserved

No artifacts when special equipment is unavailable

"A perceptual model for disparity" by Didyk et al. 2011

Eurographics 2012, Cagliari

Conclusions

- Stereo perception is complex phenomena
- Important aspects:
 - Viewing conditions
 - Viewer
 - Equipment
- Temporal coherence ...
- Different adjustment techniques:
 - Camera adjustment
 - Pixel disparity mapping operators
 - Perceptual space

Sagliari, Italy May 13-18	
Image / Video Quality	
Content	
Tunç O. Aydın Disney Research, Zurich	
<tunc@disneyresearch.com></tunc@disneyresearch.com>	
Congraphics	
Eurographics 2012, Cagilari, Italy	
Problem Definition	
Rate	
the	
Quality	
Eurographics 2012, Cagilari, Italy	
Subjective Quality Assessment	
Subjective Quality Assessment	
Figures taken from (Ferwardia 2008)	
Detection Discrimination Scaling	
Refer to: [James Ferwerda, Psychophysics 101: How to Run	
Perception Experiments in Computer Graphics, SIGGRAPH 2008].	

+ Reliable - High cost

1



Simple Distortion Metrics

- Mean Squared Error $MSE(x, y) = \frac{1}{N} \sum_{i=1}^{N} (x_i y_i)^2$ (MSE)
- Peak Signal to Noise Ratio (PSNR) $PSNR(x, y) = 10 \log_{10} \frac{L^2}{MSE}$
- Structural Similarity Index Metric (SSIM): More sophisticated, accounts for luminance contrast and structural distortions

```
SSIM(x, y) = l(\mu_x, \mu_y)^{\alpha} c(\sigma_x, \sigma_y)^{\beta} s(\sigma_x, \sigma_y)^{\gamma}
```



Perception of Distortions





Reference (bmp, 616K)

Compressed (jpg, 48K)

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Eurographics 2012, Cagliari, Italy Limitations of Simple Distortion Metrics, cont.



Visible difference doesn't always mean lower


HVS effects: (1) Glare



 Disability Glare (blooming)

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Video Courtesy of Tobias Ritschel

Disability Glare



Eurographics 2012, Cagliari, Italy (2) Light Adaptation Adaptation Level: 10⁻⁴ cd/m² Time \longrightarrow 17 cd/m² Eurographics 2012, Cagliari, Italy (3) Contrast Sensitivity Spatial Fre CSF(spatial frequency, adaptation level, temporal freq., viewing dist, ...)

Contrast Sensitivity Function (CSF)



 Steady-state CSF⁵: Returns the Sensitivity (1/Threshold contrast), given the adaptation luminance and spatial frequency [Daly 1993, Mantiuk et al. 2011].

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Generic HVS-based Quality Assessment Workflow



Visible Differences Predictor (VDP) [Daly 93, Mantiuk et al. 05, Mantiuk et al. 11], Visual Discrimation Model (VDM) [Lubin 95]



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(2) LDR pair	
HDR-VDP SSIM	
25% 50% 75% 95% 250%	
Detection Probability	

(3) HDR test, LDR reference



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Amplification of Invisible Contrast

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Eurographics 2012, Cagliari, Italy



Reversal of Visible Contrast













(4) LDR test, HDR reference



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		Eurographics 2012, Cagliari, Italy
Detecting	"types" of d	listortions
Reference	Sharpening	Blur
Loss Amplification	1 and the second se	

	Tone	Manning	Evoluation
пик	rone	mapping	Evaluation





[Aydın et al. 2008]

Generic DRI Video Quality Assessment Workflow





Extended Contrast Sensitivity Function, cont.







Extended Cortex Transform



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Evaluation of Video Tone	of HDR Mapping	Eurographics 2012. Cagliari, Italy	-	 	
HDR	82 ×		-		
HDR Reference	LDR Test	Contrast Amplification	-		
	25% 50% 75% 95%				

Evaluation of HDR Compression

Eurographics 2012, Cagliari, Italy



HDR Reference

Evaluation of HDR Compression



Medium Compression

High Compression

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25% 50% 75% 95% [Aydın et al. 2010]

Subjective Calibration * Modelfest dataset at five contrast levels

Subjective Validation

- Example [Čadík et al. 2010]
- Noise, HDR video compression, tone mapping
- "2.5D videos"
- LDR-LDR, HDR-HDR, HDR-LDR



Subjective Validation, cont.





(2) Subjects mark regions where they detect differences

Subjective vs. Objective Results Subj. Response: DRI-VQM PDM HDRVDP DRI-IQM

Subjective Validation, cont.

Stimulus	DRI-VQM	PDM	HDRVDP	DRIVDP
1	0.765	-0.0147	0.591	0.488
2	0.883	0.686	0.673	0.859
3 🔛 🞴	0.843	0.886	0.0769	0.865
4 📑	0.815	0.0205	0.211	-0.0654
5 🚮	0.844	0.565	0.803	0.689
6	0.761	-0.462	0.709	0.299
7	0.879	0.155	0.882	0.924
8	0.733	0.109	0.339	0.393
9 🔤 💽	0.753	0.368	0.473	0.617
Average	0.809	0.257	0.528	0.563

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[Čadík et al. 2010] Data available at: http://www.mpi-inf.mpg.de/resources/hdr/quality

Conclusions

- A number of established metrics are available as source code or web service - SSIM:
- https://ece.uwaterloo.ca/~z70wang/research/ m/
- HDRVDP : http://sourceforge.net/projects/hdrvdp/files/hdr
- DRI-IQM and DRI-VQM:
 <u>http://drim.mpi-inf.mpg.de/</u>
- Researchers are starting using these metrics instead of user studies.
- Future directions:
- Metrics for retargeted images [Liu et al. 2011]
 Better HVS models [Mantluk et al. 2011]
- Smarter distortion measures.