UNIVERSITY OF
FORWARD
THINKING
WESTMINSTER

Bridging the gap between image quality and aesthetics

Prof. Sophie Triantaphillidou

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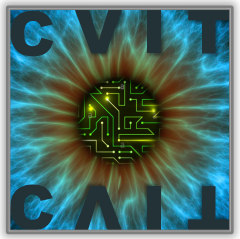
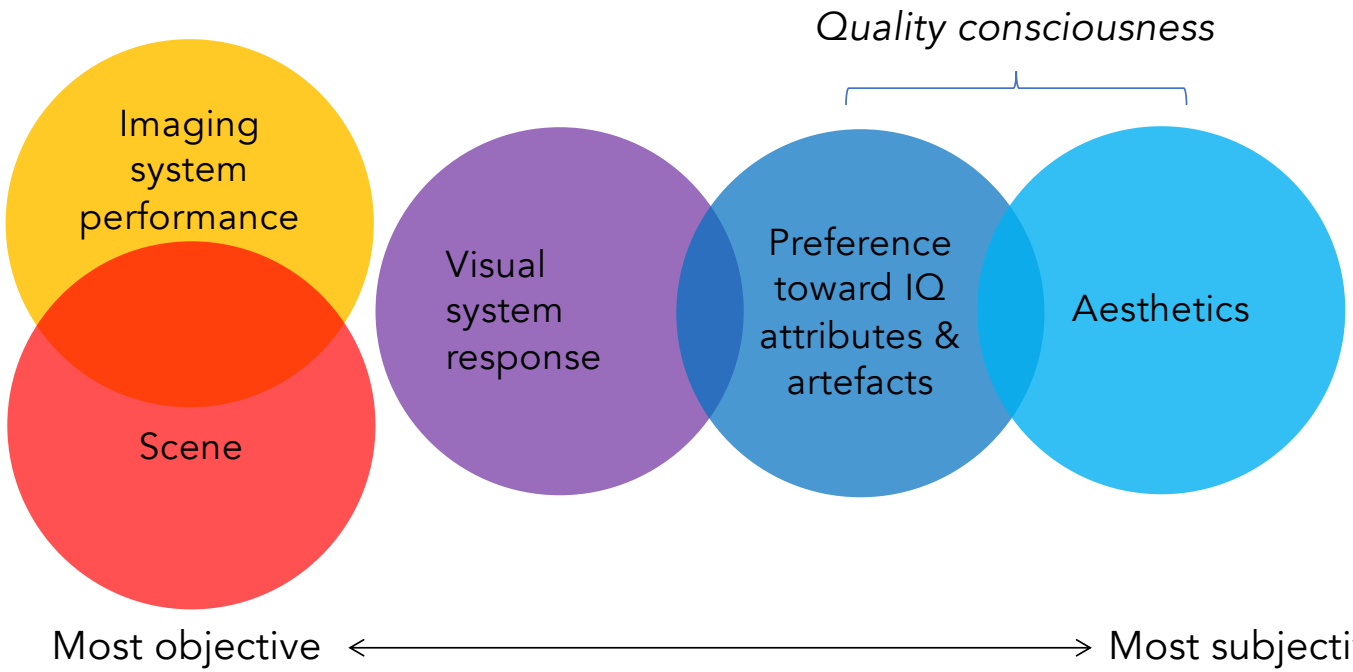


ICC London Meeting. April 2023

Image Quality

"the perceived 'goodness' (value) of an image, viewed by an observer, under a given environment and context"



Adapted from Fry, E., Triantaphillidou, S., et. al 2019

Image quality evaluation

Subjective

- Visual psychophysics
- Large number of observers
- Range of scene contents

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Objective – Image Quality Models/Metrics

- **computational** → extract information / model **natural scene images**
  model visual system
  not concerned with modelling imaging system

- **engineering (mechanistic)** → extract information from **test image** / model imaging system
  model visual system (+ visual data calibration)
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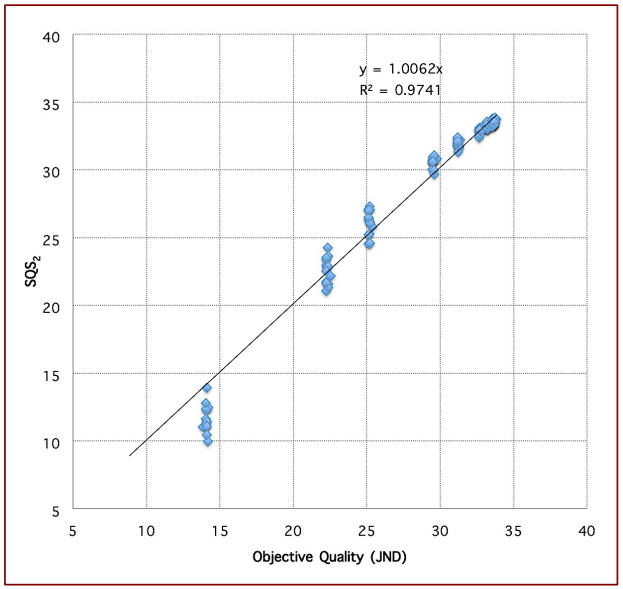
IQM system-dependent but scene content independent

Image quality evaluation



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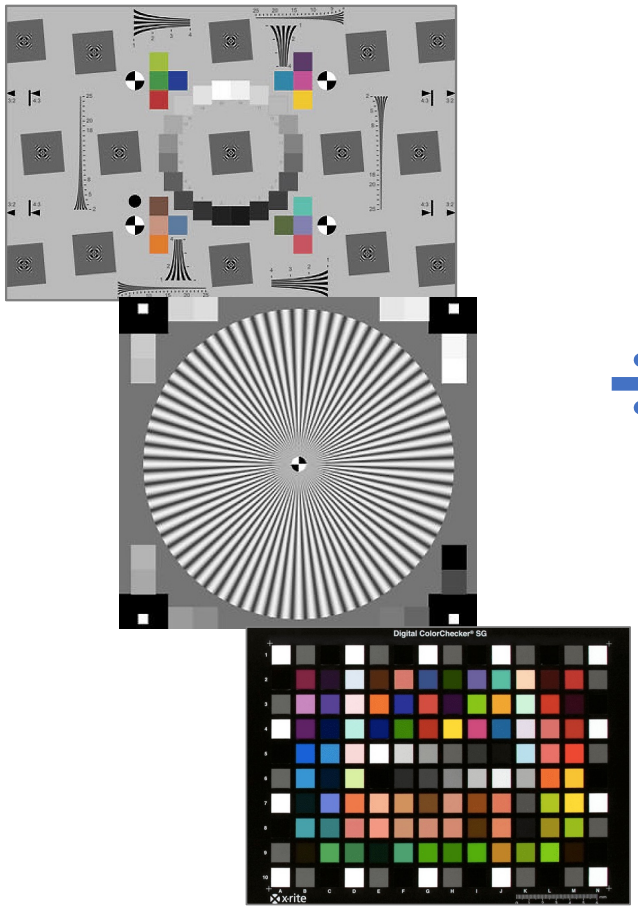
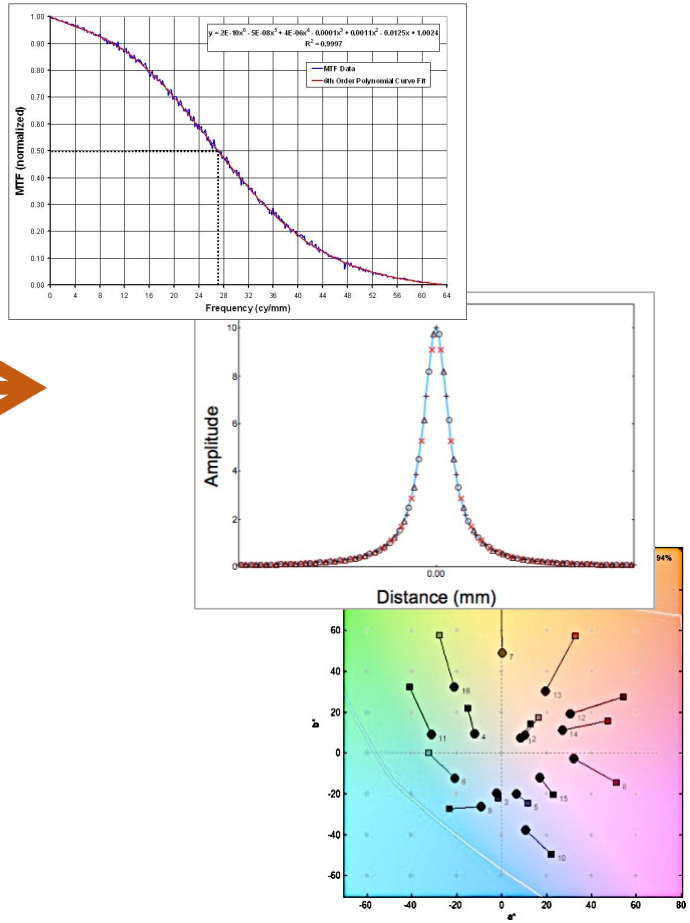
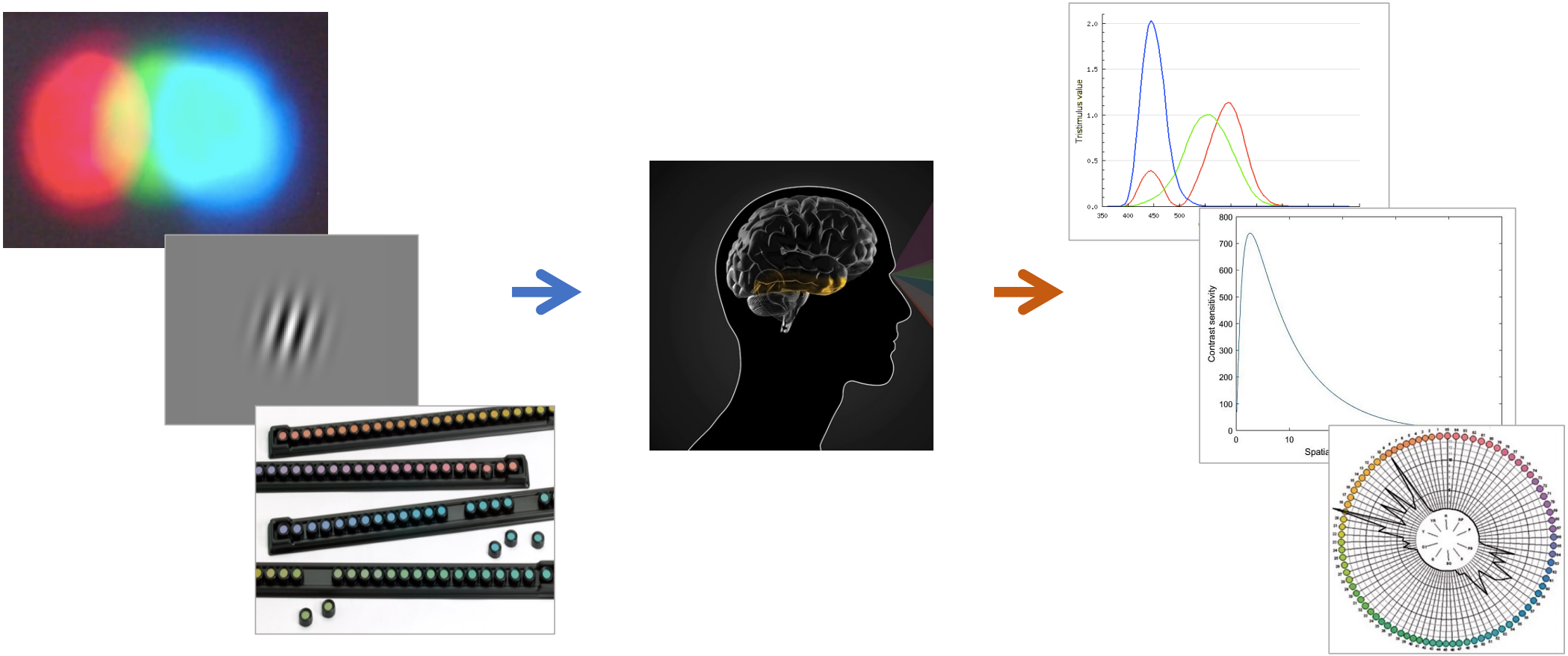
Imaging system performance measurement

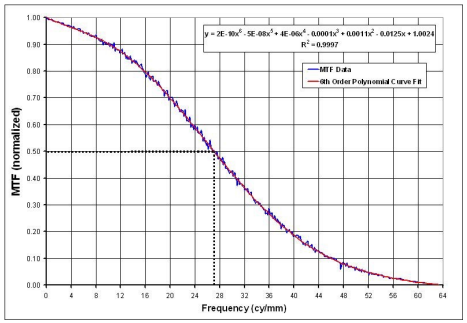


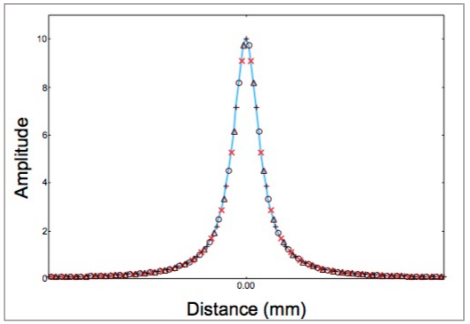


Visual system measurement

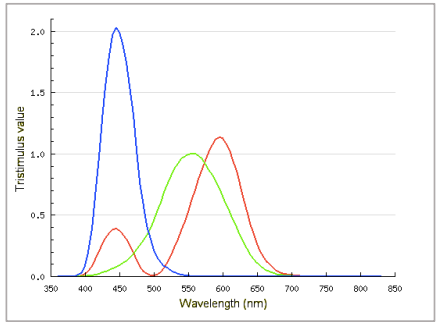


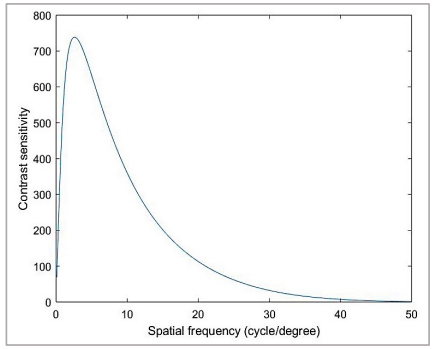
Engineering image quality metrics / models



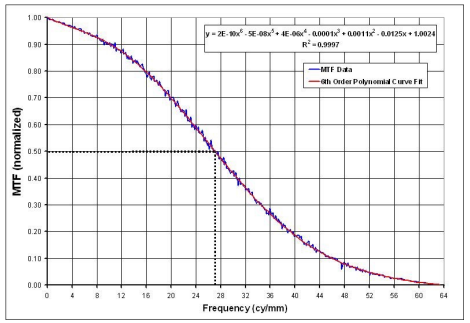


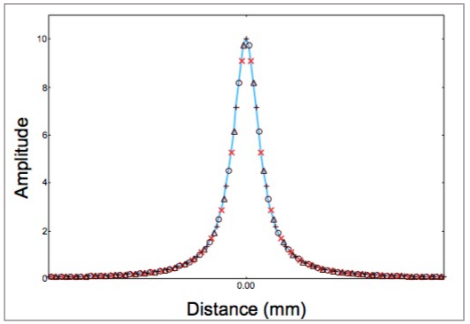
IQM
system-dependent
scene content independent





Engineering image quality modeling





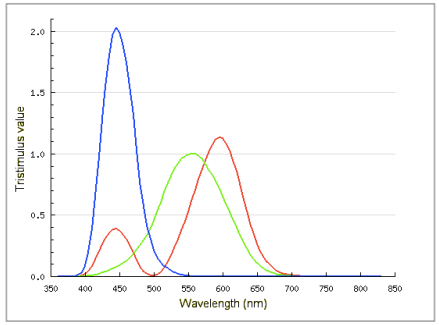
IQM
system-dependent
scene content independent

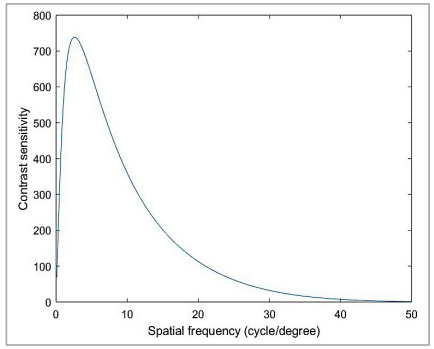
IEEE 1864 CPIQ
acutance, visual noise
texture blur, chroma level

IEEE P2020 Automotive IQ
acutance, visual noise
texture blur, flare

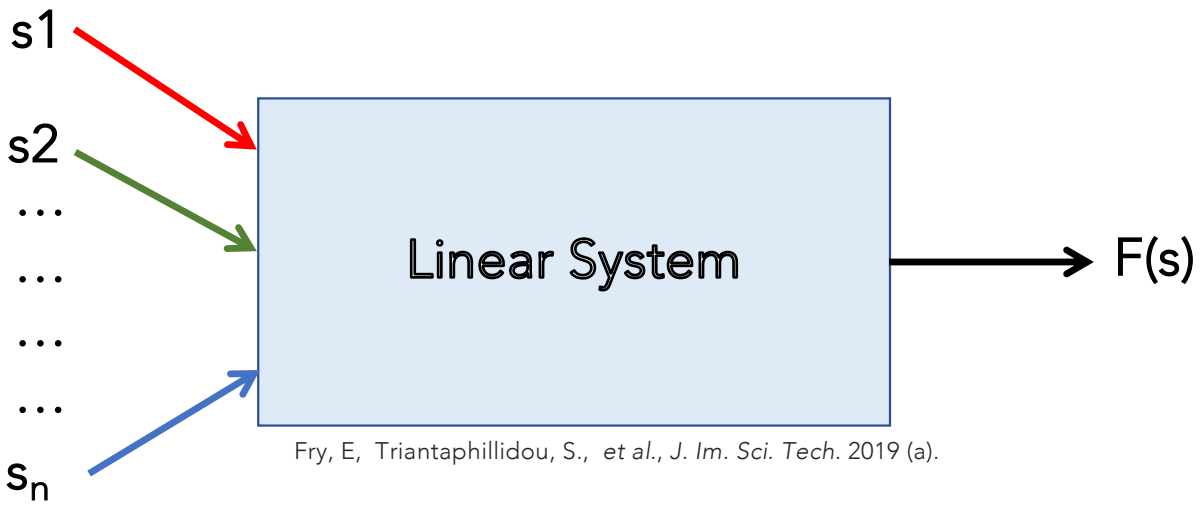
CIE
DE94, CIEDE2000

Others
ISO 12233 acutance
SQF
NEQ
…



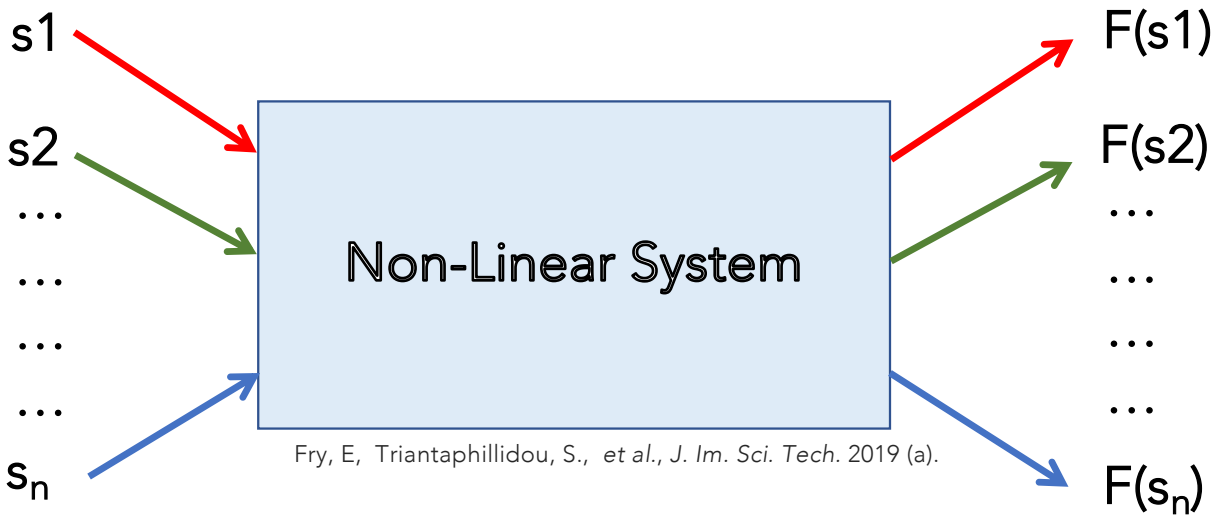


Linear vs non-linear content aware systems



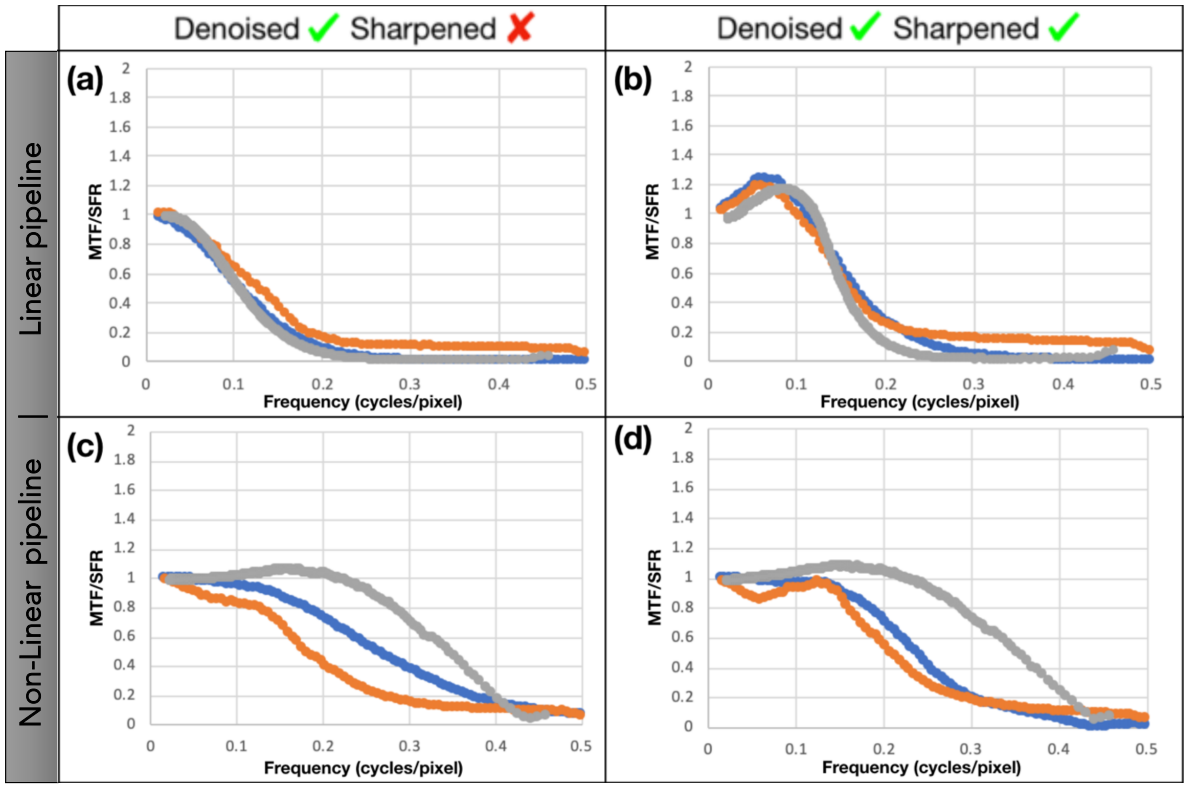
Fry, E, Triantaphillidou, S., *et al.*, *J. Im. Sci. Tech.* 2019 (a).

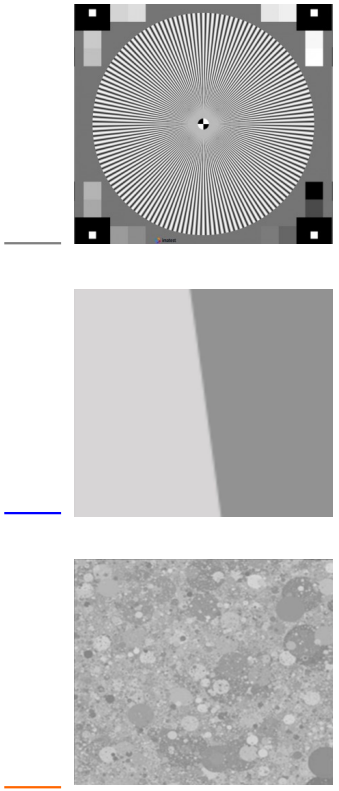
Linear vs non-linear content aware systems



Fry, E, Triantaphillidou, S., *et al.*, *J. Im. Sci. Tech.* 2019 (a).

Measuring camera sharpness/resolution - MTF

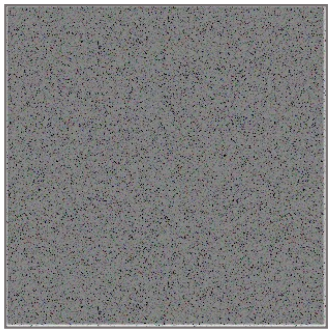


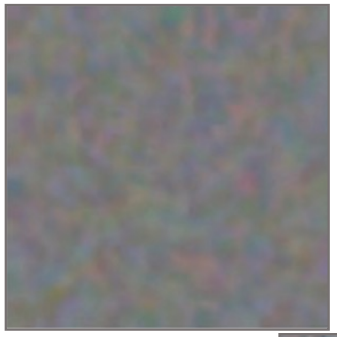


Fry, E., *PhD Thesis*, 2020

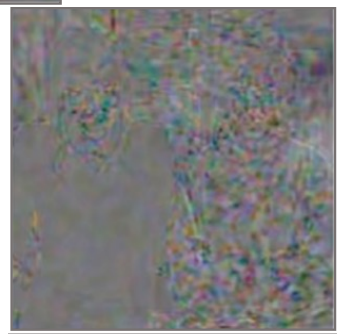
Scene dependent *noise* variations

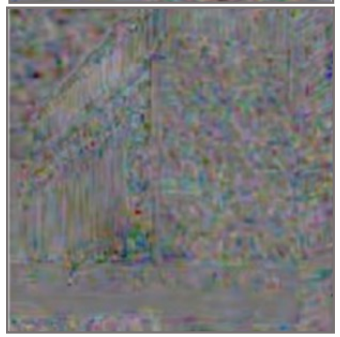
Input





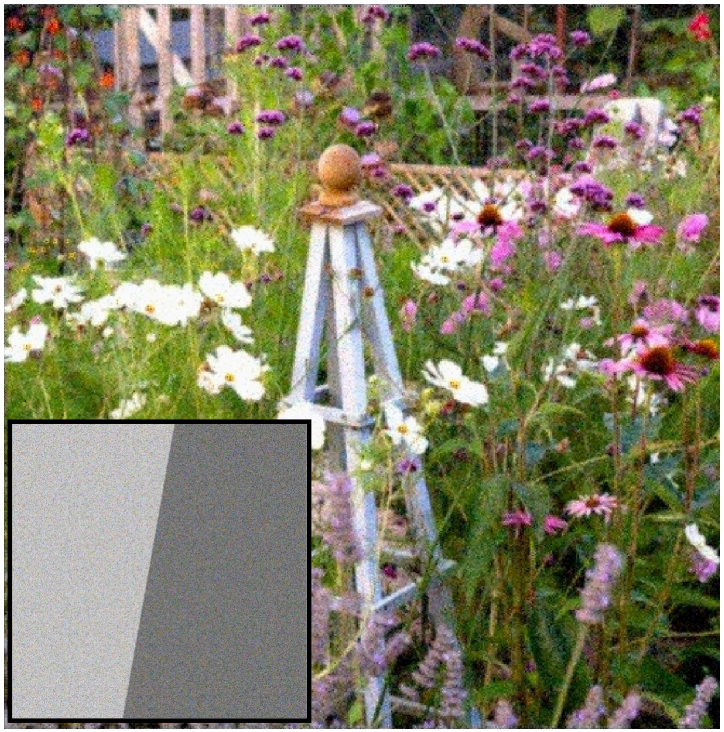
Output noise
(after denoising)





Scene dependent *sharpness* variations

Input



Output image
(after denoising)

Scene dependent tone variations

HDR image after
burst fusion

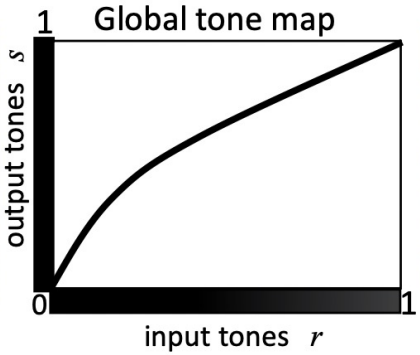
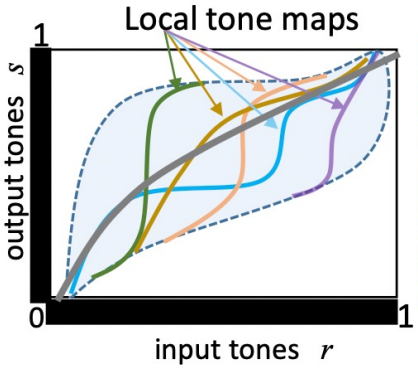


Image after *global*
tone mapping applied



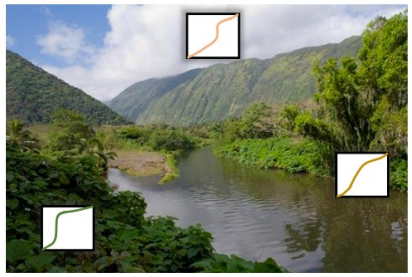


Image after *local*
tone mapping applied

Mobile Computational Photography: A Tour
Delbracio et al., CVPR, 2021

Scene-and-process dependent IQ models

Use imaging performance measures:

- Conform to current (industry) standards
- Account for non-linear, content aware imaging system performance

Scene dependent image quality modeling

Use imaging performance measures:

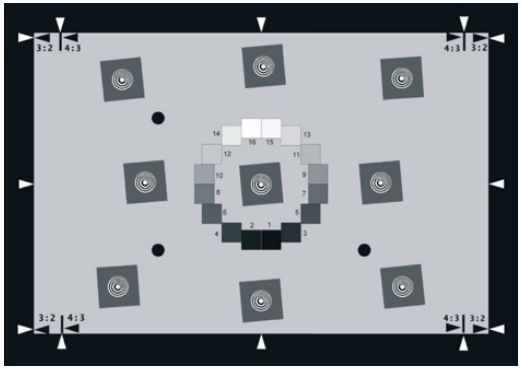
- Conform to current (industry) standards
- Account for non-linear, content aware imaging system performance

Use scene dependent visual system models:

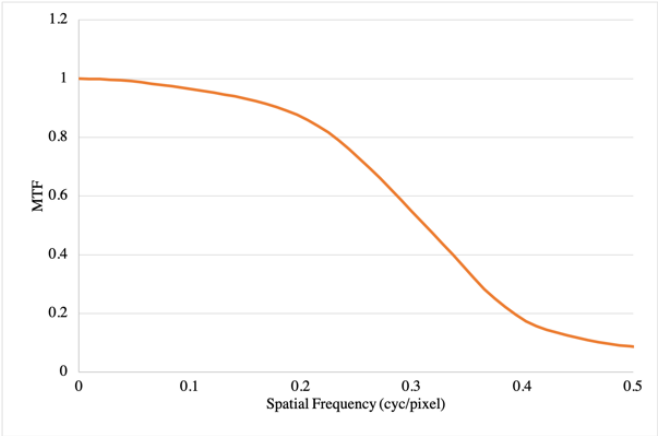
- Such as the spatial CSF
- While accounting for scene content parameters

MTF/SFR camera performance

Input Test Chart



Measured MTF



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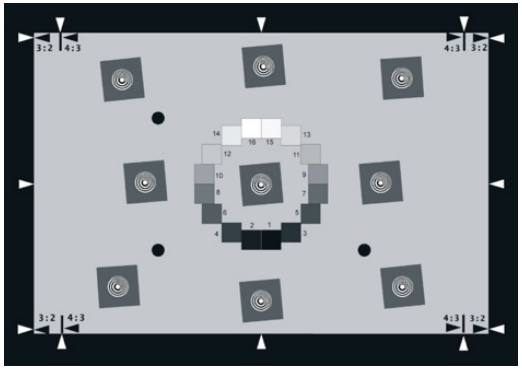
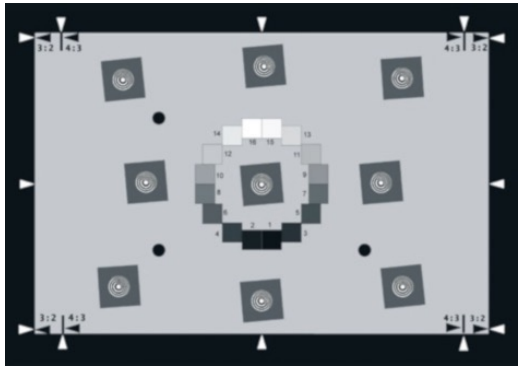


Output Test Image



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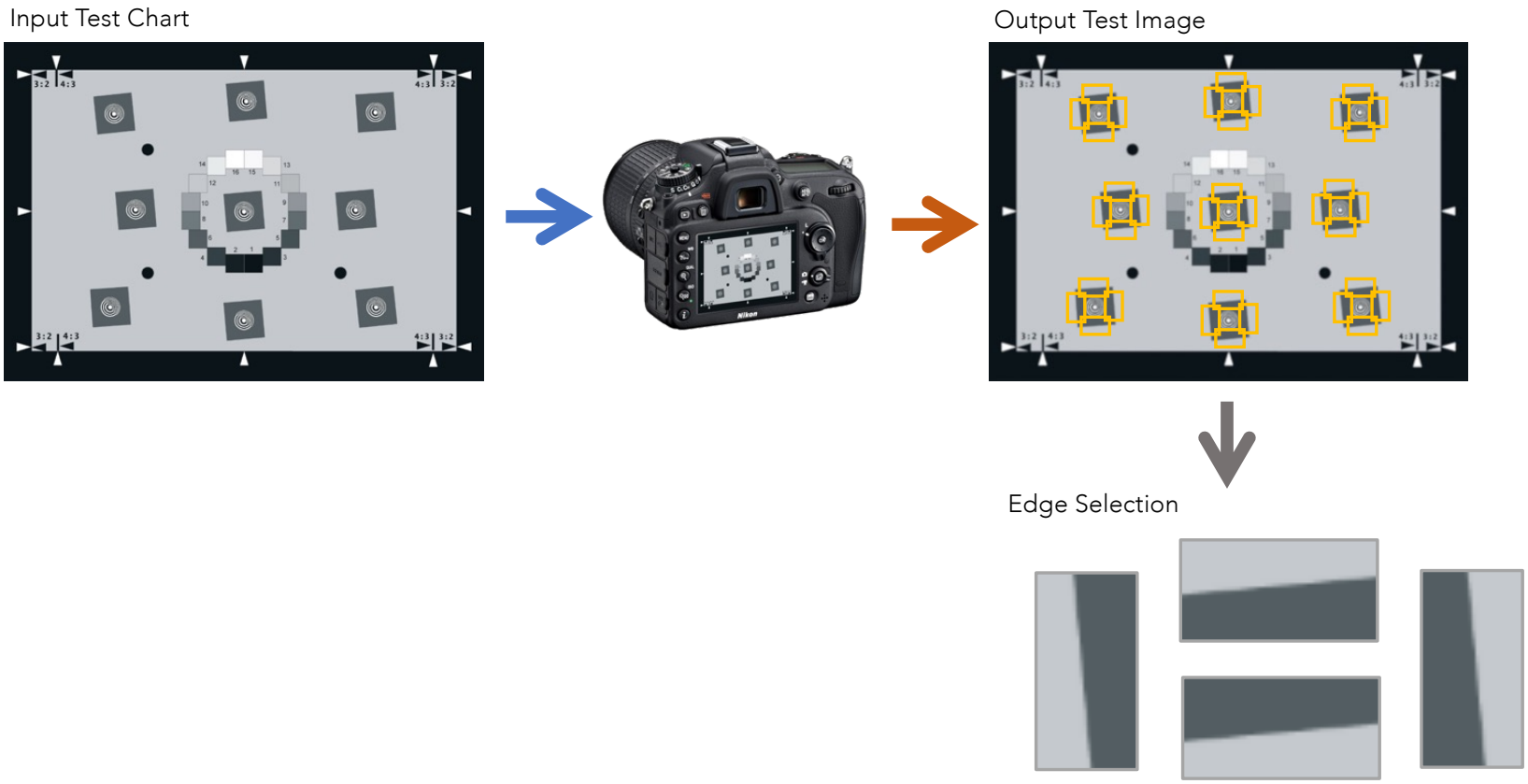

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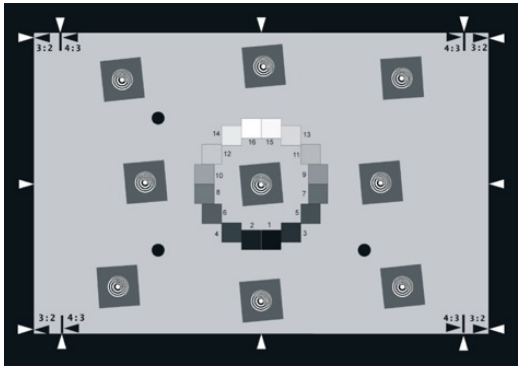

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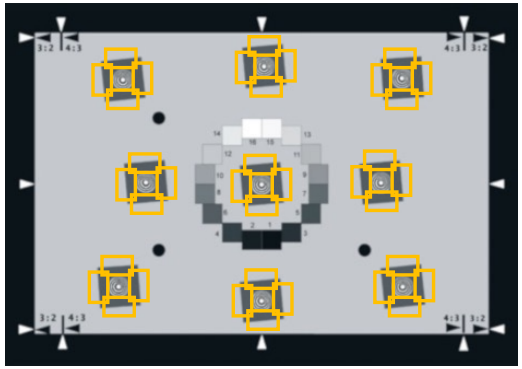
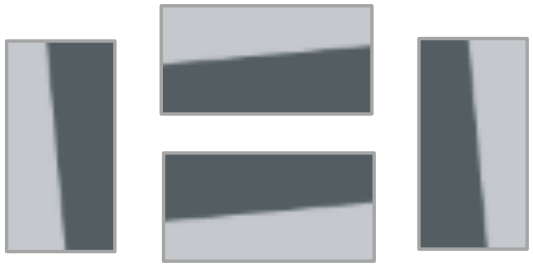
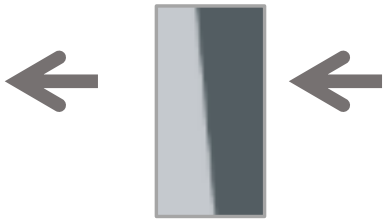


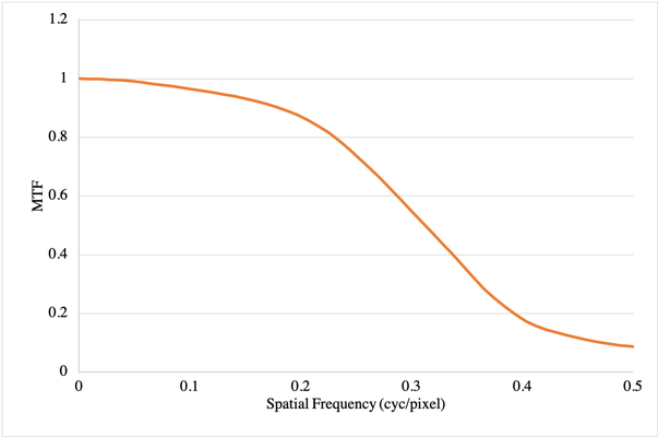
Edge Selection



ISO 12233 e-SFR calculation



Measured MTF



MTF/SFR camera performance *from natural scenes*

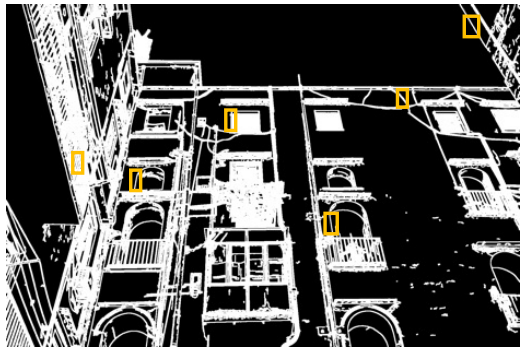
Input Natural Scene

Output Natural Image

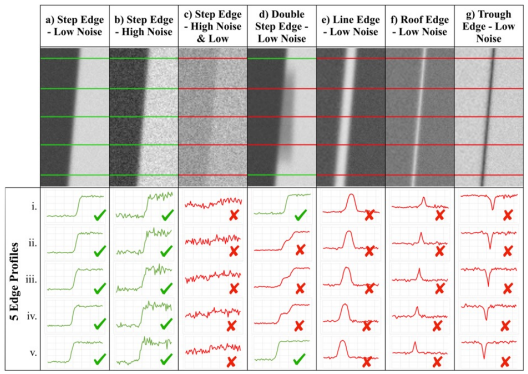
MTF/SFR camera performance *from natural scenes*

Input Natural Scene

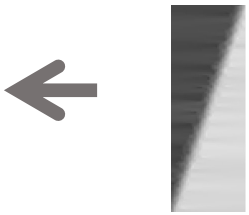
Edge Image



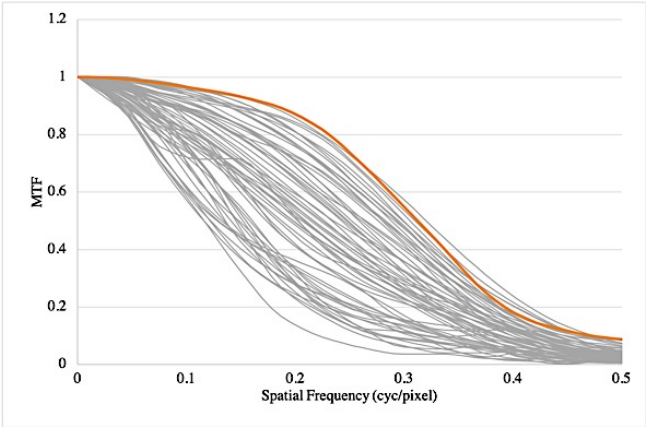
Edge Selection, Isolation and Verification



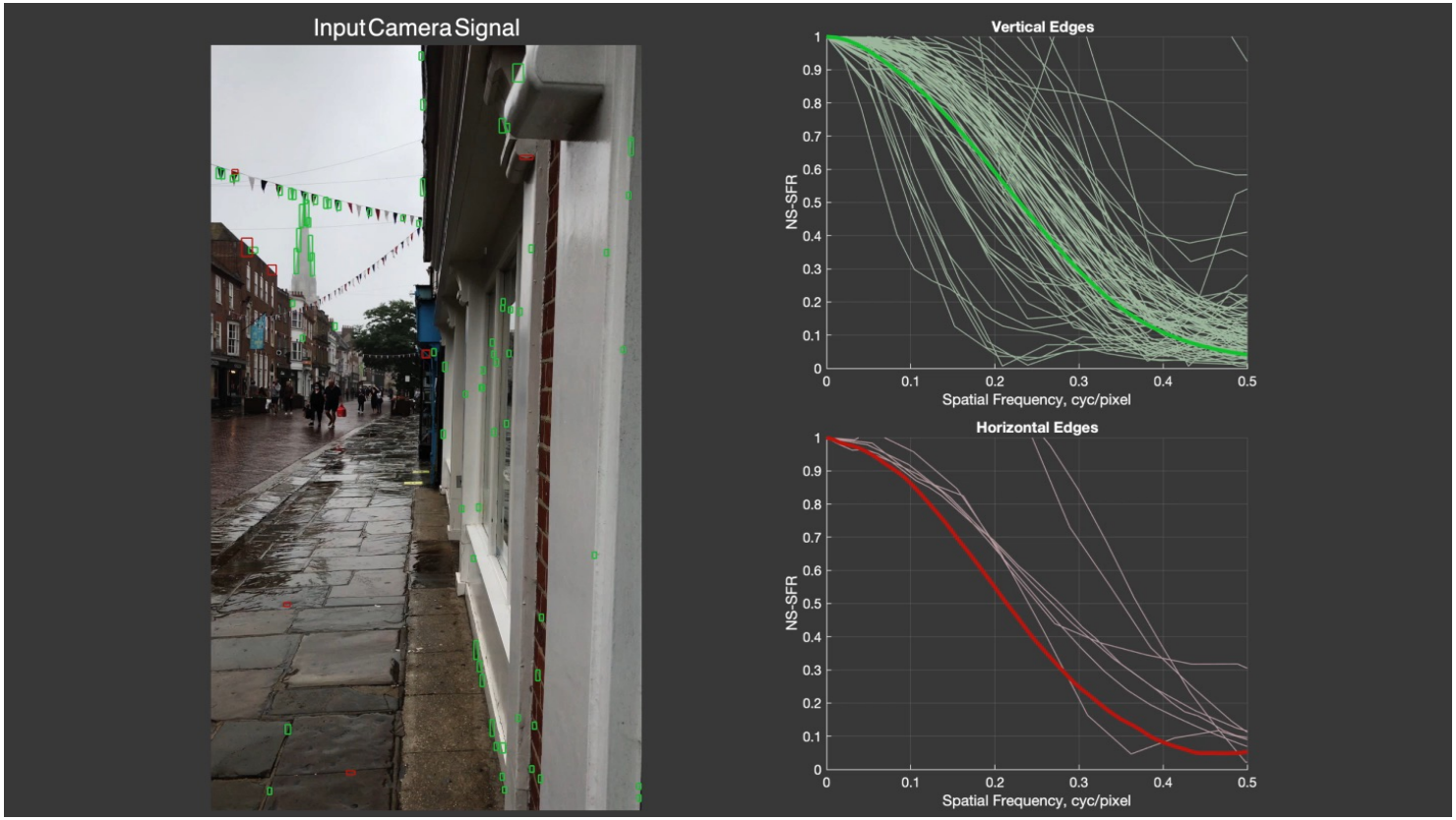
ISO 12233 e-SFR calculation



Natural scene MTF (NS-SFR)

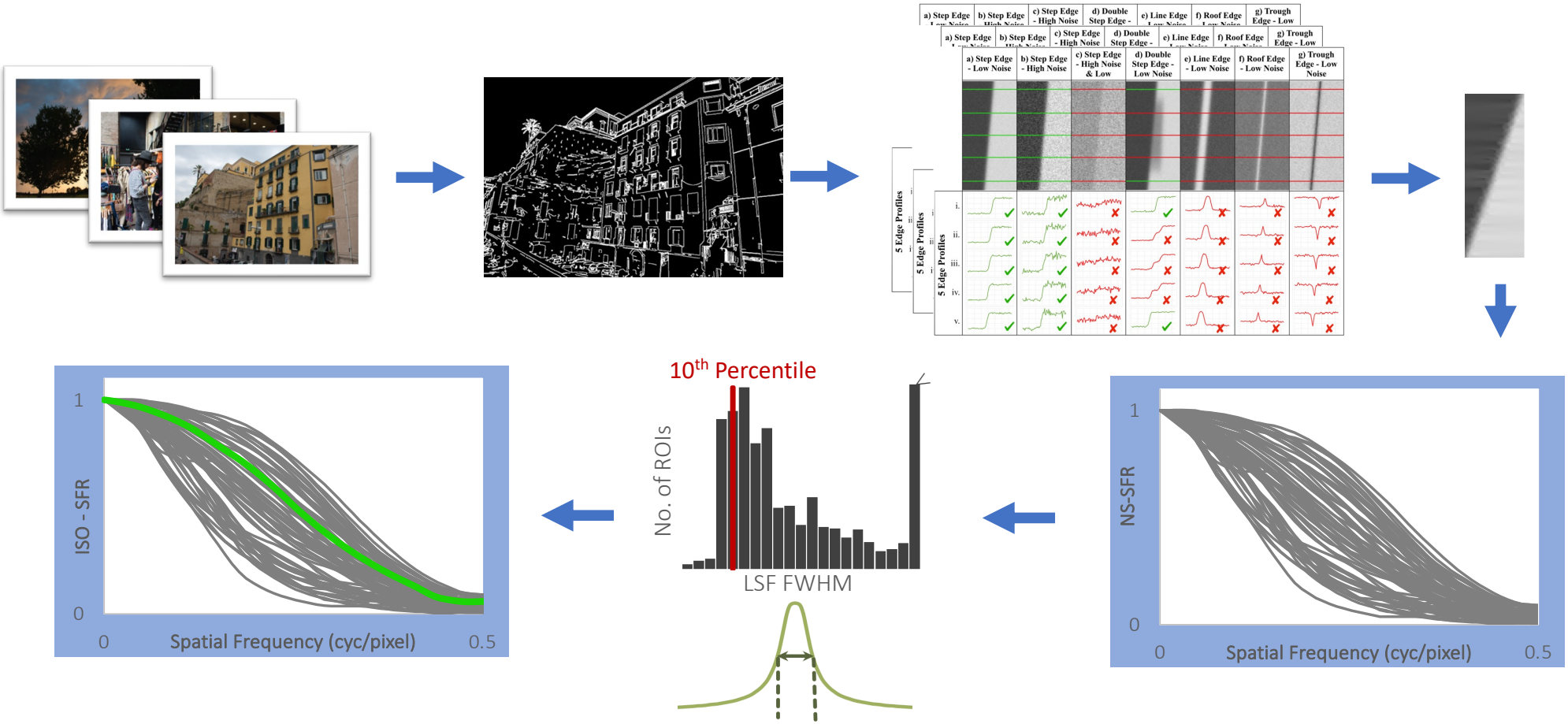


MTF/SFR camera performance *from natural scenes*



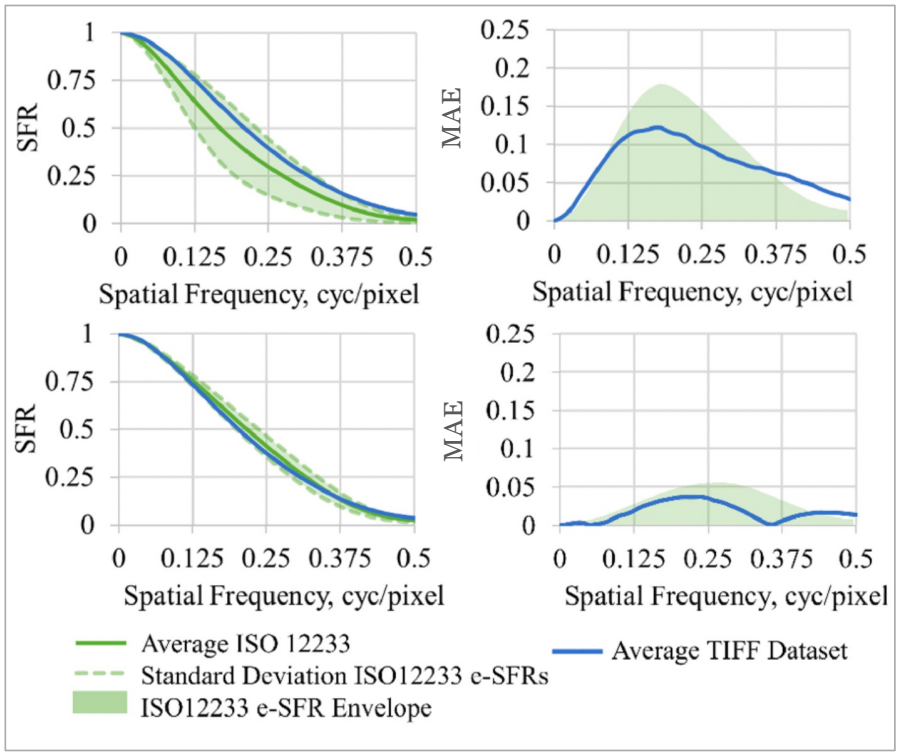
This is a concept demo.
The processing was not implemented live.
by Oliver vanZwanenberg

MTF/SFR camera performance *from natural scenes*



MTF/SFR camera performance *from natural scenes*

2 x DSLR camera systems (near-linear)



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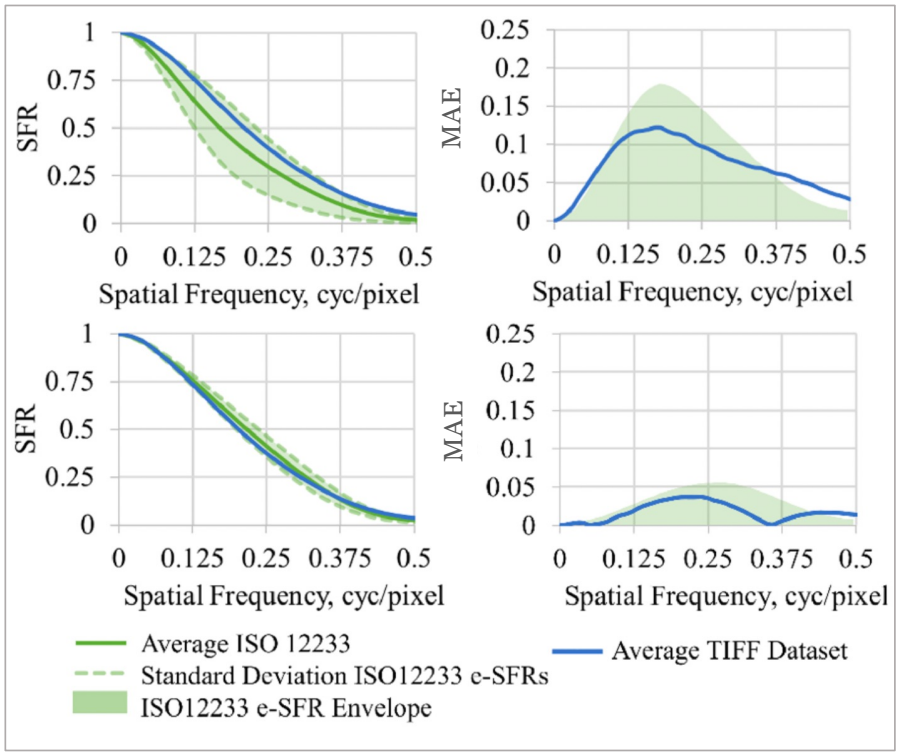
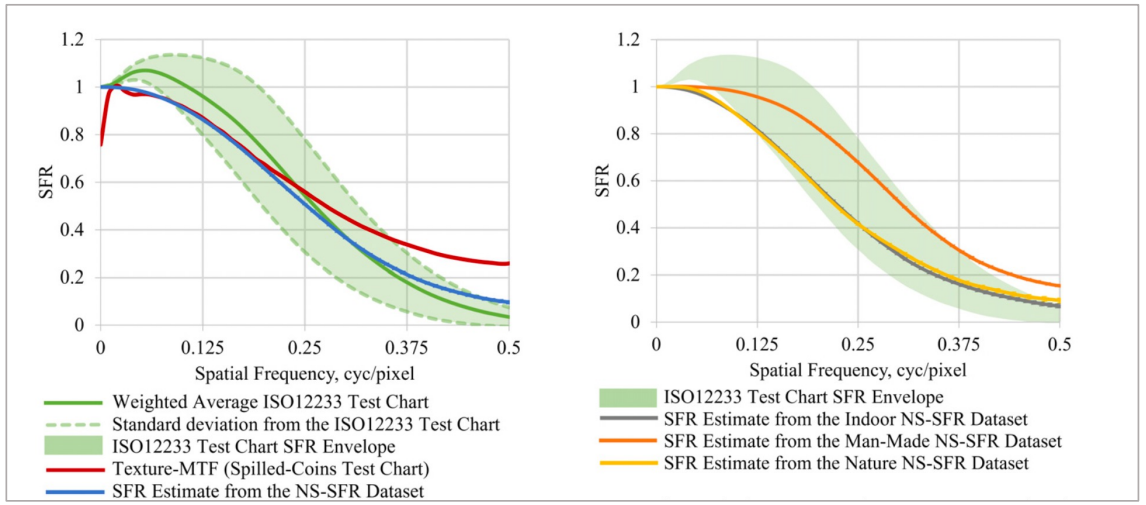


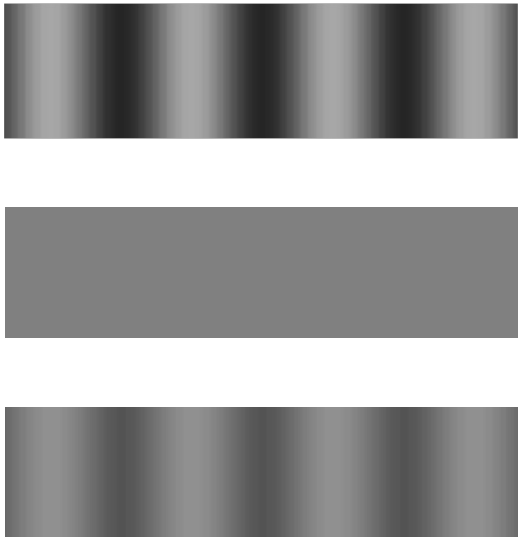
iPhone camera system (highly non-linear)



- van Zwanenberg, O., Triantaphillidou, S., Jenkin, R. and Psarrou, A. (2021), *Estimation of ISO12233 Edge Spatial Frequency Response from Natural Scene Derived Step-Edge Data*, Journal of Imaging Science and Technology, 65 (6), pp. 60402-1-60402-16.
- van Zwanenberg, O., Triantaphillidou, S., Psarrou, A. and Jenkin, R, (2021), *Analysis of Natural Scene Derived Spatial Frequency Responses for Estimating Camera ISO12233 Slanted-edge Performance*, Journal of Imaging Science and Technology, 65 (6), pp 60405-1 – 60405-12.

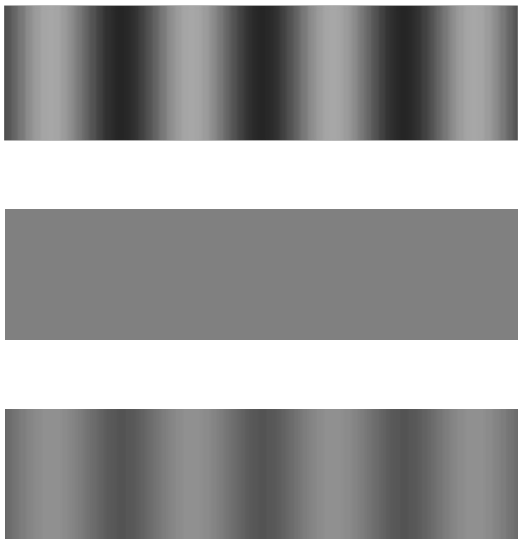
Scene dependent visual measures

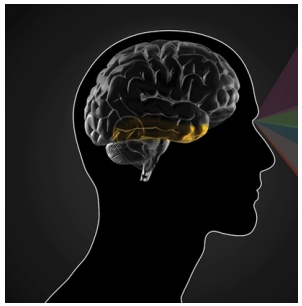
Contrast Sensitivity Function (CSF) } Threshold contrast sensitivity

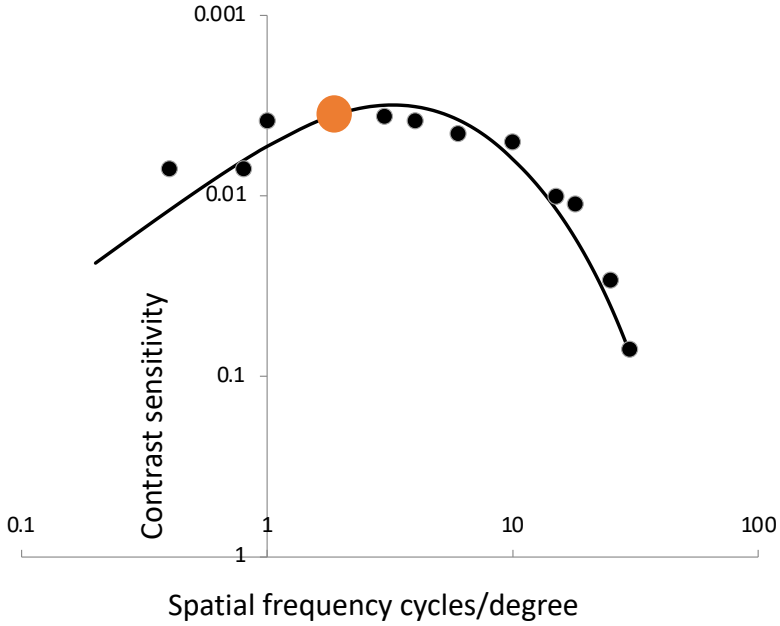


Scene dependent visual measures

Contrast Sensitivity Function (CSF) } Threshold contrast sensitivity



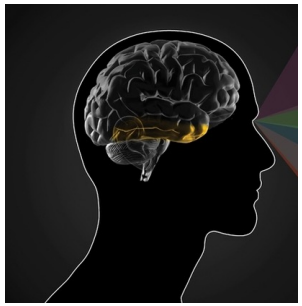




Scene dependent visual measures

Isolated Contrast Sensitivity Function (iCSF)

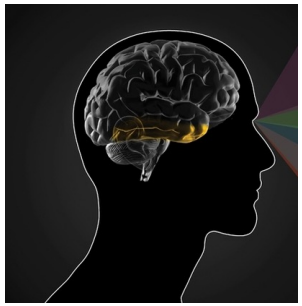
Threshold contrast sensitivity

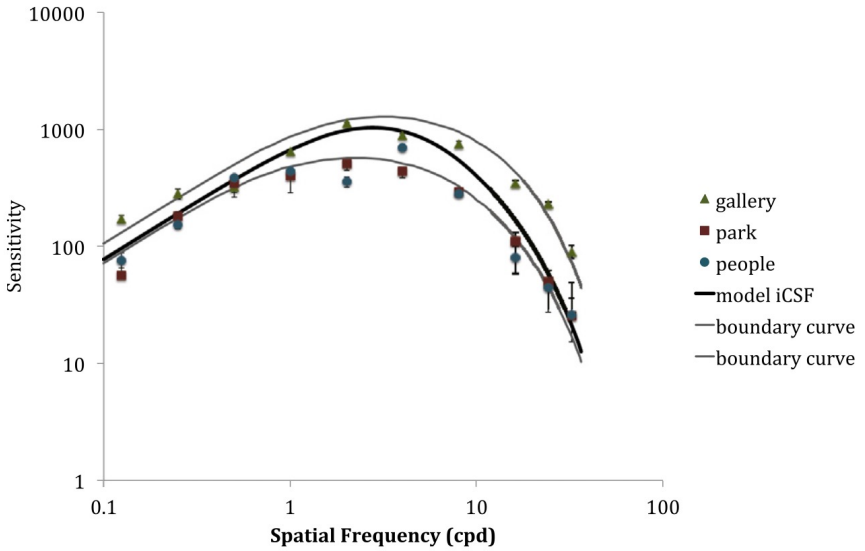


Scene dependent visual measures

1. **Isolated** Contrast Sensitivity Function (iCSF)

Threshold contrast sensitivity

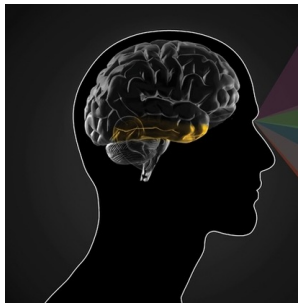


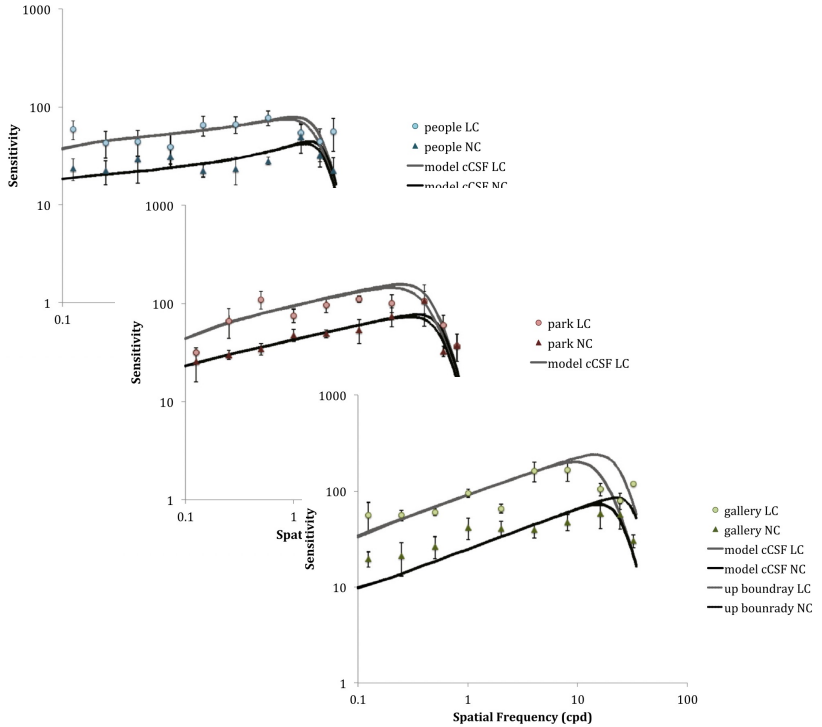


Scene dependent visual measures

2. **Contextual** Contrast Sensitivity Function (cCSF)

Threshold contrast sensitivity





Scene dependent visual measures

Isolated **Contrast Sensitivity** Function (iCSF)

Contextual **Contrast Sensitivity** Function (cCSF)

Threshold contrast sensitivity

Models account for scene contrast spectra

Triantaphillidou, S., Jarvis, J. R., Psarrou, A. and Gupta, G. (2019) *Contrast sensitivity in images of natural scenes*, Signal Process Image, Signal Processing: Image Communication, 75, pp. 64-75.

Scene dependent visual measures

Isolated **Contrast Sensitivity** Function (iCSF)

Contextual **Contrast Sensitivity** Function (cCSF)

Threshold contrast sensitivity

Models account for scene contrast spectra

Triantaphillidou, S., Jarvis, J. R., Psarrou, A. and Gupta, G. (2019) *Contrast sensitivity in images of natural scenes*, Signal Process Image, Signal Processing: Image Communication, 75, pp. 64-75.

Isolated **Contrast Discrimination** Function

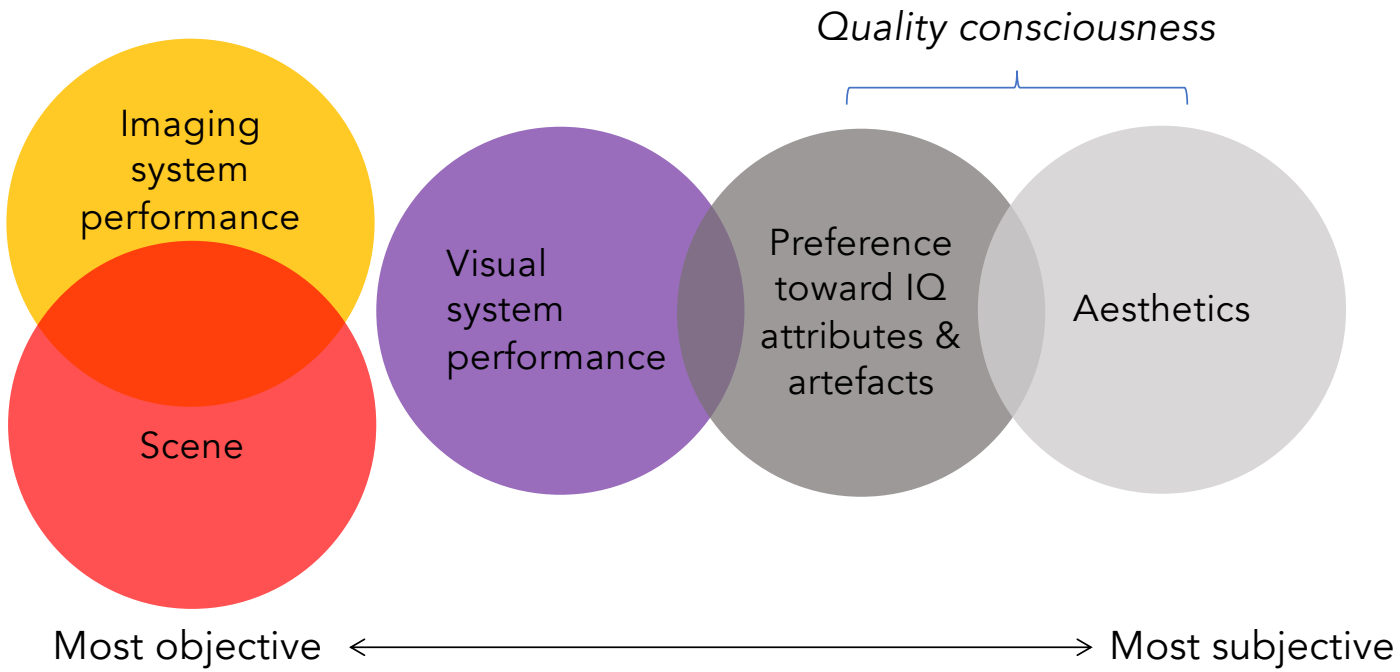
Contextual **Contrast Discrimination** Functions

Supra-threshold sensitivity

Models account for cCSF & scene contrast spectra

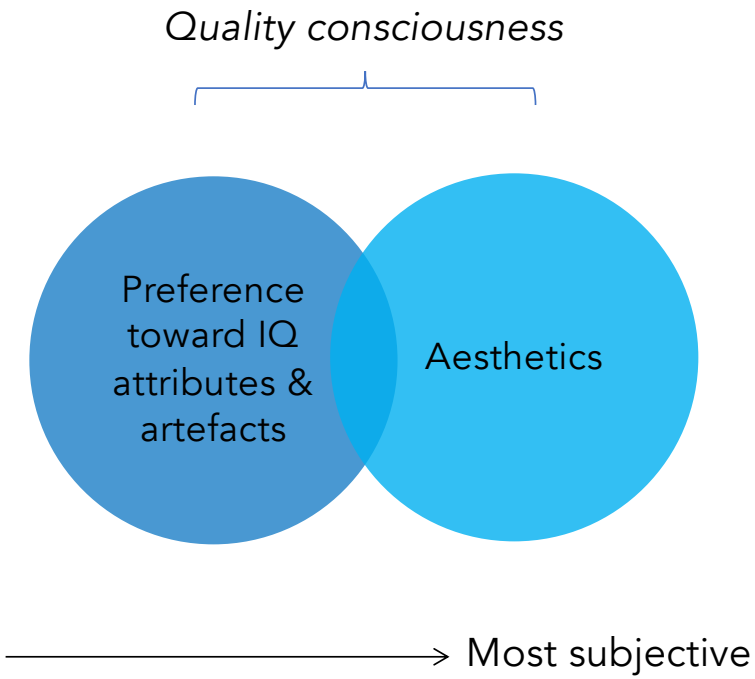
Jarvis, J., Triantaphillidou, S. and Gupta, G. (2022), *Contrast discrimination in images of natural scenes*, Journal of the Optical Society of America A. 39 (6), pp. B50-B64.

Image Quality modeling



Preference and Aesthetics

- Context dependent
- Culture dependent
- Industry/manufacturer dependent
- Personal
- Change with time
  - Fashion trends
  - Imaging system evolution



Computational aesthetics

"aim to identify or evaluate visual aesthetic expressions in images using algorithms"

- Composition
  - Rule of thirds
  - Golden ratio
  - Focus, focal length, depth of field
- Features
  - Colour
  - Exposure/luminance
  - Edges/textures/sharpness/contrast
- Contents

Evolution of photographic aesthetics

- Analysis of **contemporary** photographic collections to track preference & aesthetics
- Large collections
- Commercial photographic agencies (providing images worldwide)
- 40-50 years period
- Curated image collections (aesthetic value)
- Compare findings with literature (art & science)

SCIENCEphotoLIBRARY IMAGE SOURCE plainpicture

nature picture library Millennium Images

SCIENCEphotoLIBRARY

Evolution of photographic aesthetics

A. Nature
    1. Wildlife
    2. Seasonal Landscapes
    3. Underwater Seascapes
    4. Night Sky
    5. Aerial Landscapes
    6. Close-ups

B. People
    1. Portraits (close ups)
    2. Groups of people

C. Satellite

D. Abstracts
    1. Microscopic
    2. Macroscopic
    3. Textures/detail

SCIENCEphotoLIBRARY

Evolution of photographic aesthetics

A. Nature
   1. Wildlife
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D. Abstracts
   1. Microscopic
   2. Macroscopic
   3. Textures/detail

Evolution of photographic aesthetics

Examine color computational aesthetic features

- Colorfulness (CFL) - linear combination of chromaticity variance and chroma magnitude
- Color harmony (CH) - based on the frequency of appearance of color patterns
- Opposing or opponent color (OC)
- Complementary colors (CC)
- Dominant colour palettes (PCP) – based on clustering, and subsequent analysis

Evolution of photographic aesthetics

Discover

- How "portrait" skin tone rendering varied with time & variation between photo agencies
  - Decade trends
  - Culture trends
  - Effect of medium

Evolution of photographic aesthetics

Discover

- How "portrait" skin tone rendering varied with time & variation between photo agencies
  - Decade trends
  - Culture trends
  - Effect of medium
- Colour trends in "abstracts" category – are they identified, any discoveries?
  - Balance
  - Rhythm/pattern
  - Variety
  - Contrast
  - Movement
  - Surprise

Evolution of photographic aesthetics

Further work will examine

- Most (all) categories
- Attributes
  - image complexity
  - rule of thirds
  - golden ratio
  - diagonal and leading lines
  - focus and depth of field
- Hand crafted features and potential AI tools
- Compare computational findings with literature findings on photo aesthetics

Summary

- Image quality involves scene contents, imaging chain, human vision and cognition
- Image quality modelling, viewed from a **mechanistic** viewpoint, requires investigation of all abovementioned elements and their interrelationships
- Developed scene-and-system-dependent **performance measures** (spatial -> MTF and NPS)
- Developed scene-dependent (**spatial) visual models**
- Initial testing on benefit of such models in IQMs modeling is very positive
- Moving from scene-dependent imaging performance modelling to modelling preference and aesthetics bridges a gap
- Track aesthetics in contemporary photography using computational means and photo collections with known aesthetic values

Colleagues

Dr Aleka Psarrou, Reader, UoW

Dr John Jarvis, visiting Professor, UoW

Dr Robin Jenkin, visiting Professor, UoW (Nvidia, CA)

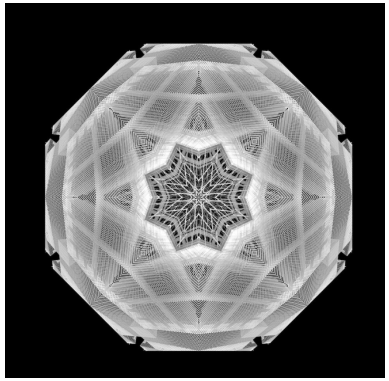
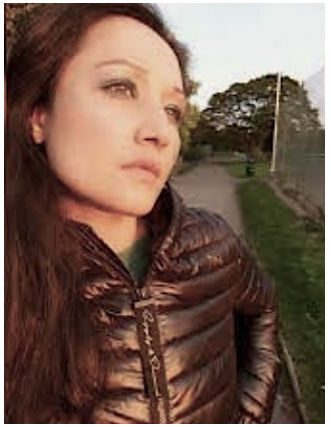


Photo: Edward Fry



Dr Oliver vanZwanenbegr, PhD graduate (now @ Onsemi, UK)

Dr Edward Fry, PhD graduate (now @ Apple, CA)

Adela Shah, PhD student

Thank you!

- van Zwanenberg, O., Triantaphillidou, S. and Jenkin, R. (2023), *A tool for deriving camera spatial frequency response from natural scenes (NS-SFR),* IS&T Electronic Imaging Symposium: Image Quality & System Performance conference XX, San Francisco, California, USA.
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- Fry, E. W. S., Triantaphillidou, S., Jenkin, R. B., Jacobson, R. E. and Jarvis, J. R. (2020), *Noise Power Spectrum Scene-Dependency in Simulated Image Capture Systems*, In: IS&T Electronic Imaging Symposium: Image Quality & System Performance conference, San Francisco, California, USA.
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