Encoding Color Difference Signals for High Dynamic Range and Wide Gamut Imagery

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Outline

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3) Model
   1) Data sets
   2) Cost functions

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Introduction

Find a **most efficient encoding for HDR color imagery** co-optimized for

- Efficient Color Encoding &
- Color Volume Mapping (Tone- and Gamut-Mapping)
Why color volume mapping?

Example HDR Mastering Display
- Rec.2020
- 0.005-4000cd/m²
- Dark environment

Example Tablet
- Rec.709
- 0.1-400cd/m²
- Bright environment

Example HDR-TV
- ~P3
- 0.01-1000cd/m²
- Dark environment
Requirements to an HDR color encoding

- 0.005 – 10,000 cd/m² dynamic range
- Minimum Rec.2020 gamut – better be able to encode all colors
- Efficient quantization – ‘JND-uniformity’
- Static encoding (not content or viewer dependent)
- Low computational complexity (mobile devices)
- Decorrelate the achromatic axis (for color subsampling)
- Hue-linear (for gamut mapping)
Related work

- “PQ” / SMPTE ST.2084 [1]

- PQ is a **luminance encoding scheme** that quantizes according to the minimum step beyond the visibility threshold according to the Barten’s contrast sensitivity model [2]

- It follows the peak contrast sensitivity for any adaptation state
Model selection

**IPT**

- Motivated by human perception
- Optimized for hue-linearity
- LMS – cone response
Model selection

$Y' C_b C_r$

- **RGB** - physically realizable display primaries
- Color differencing scheme

Typical digital projector primaries (Barco DP90 & DP90KP dashed)
Selecting a Model

\[ IC_{aC_b} \]

- Low computational cost
- Well known from \( YC_{bC_r} \) & IPT in encoding and color communities
- Already implemented in a large number of devices
Selecting a nonlinearity

By model definition, the achromatic case is true when \( R = G = B \)

In consequence the nonlinearity (\( \mathbf{M}_2 \)) must be PQ to guarantee an optimal encoding along the achromatic axis
Finding the Model Parameters

\[ IC_aC_b \]

- But how to find the best matrix parameters?

- Optimization

- $\rightarrow$ Need training and test set as well as cost functions
Data sets: Isoluminance

Test set:
- Comparable to Kindlmann\textsuperscript{[3]} but:
  - near Rec.2020 gamut
  - HDR (up to \(\sim 2000\text{cd/m}^2\))

Verification set:
- Kindlmann 2002\textsuperscript{[3]}
Data sets: Hue linearity

Test set:
- Setup as Hung & Berns but:
  - near Rec.2020 gamut
  - HDR (up to ~2000cd/m²)

Verification set:

FIG. 3. Monitor layout for the experiment.
Data sets: JND uniformity

Test set:
- Step edge pattern on stimuli background in dark environment using method of adjustment
  - P3 gamut
  - HDR (0.005 - 1000cd/m²)

Verification sets:
- Kim 2013 [6]
Finding the matrix parameters

Isoluminance cost function:

- Mean squared difference in predicted intensity between equiluminant patches

\[ C_{il} = \frac{1}{n} \sum_{i=1}^{n} (I_{i,1} - I_{i,2})^2 \]

where \( I_{i,1} \) and \( I_{i,2} \) are the intensities for \( n \) color pairs that were adjusted by human observers to have the same perceived luminance.
Finding the matrix parameters

Hue linearity cost function:

\[ h_{i,j} = \text{atan2}(C_{a,i,j}, C_{b,i,j}) \]

\[ s_{i,j} = \sqrt{(C_{a,i,j})^2 + (C_{b,i,j})^2} \]

\[ C_{hl} = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} \left( \frac{h_{i,j} - \frac{1}{m} \sum_{w=1}^{m} h_{i,w}}{\frac{1}{nm} \sum_{u=1}^{n} \sum_{v=1}^{m} s_{u,v}} \right)^2 \]

where \( h_{i,j} \) and \( s_{i,j} \) are the hue and saturation in the new color space for \( n \) color tuples of \( m \) elements. Human observers adjusted all \( m \) elements of each tuple to have the same perceived hue.
Finding the matrix parameters

Hue linearity cost function:

- Mean squared distance of predicted hue to the mean predicted hue. (for samples that have been adjusted to have the same hue by human observers)
Finding the matrix parameters

JND uniformity cost function:

- Variance in JND-ellipsoid half axes length after SVD

\[
C_{\text{jnd}} = \frac{1}{3n} \sum_{j=1}^{3} \sum_{i=1}^{n} \left( \frac{1}{3n} \sum_{u=1}^{n} \sum_{v=1}^{3} \|q_{ij}u\| - 1 \right)^2
\]

where \(q_{ij}\) are the three half axes of \(n\) JND ellipsoids after singular value decomposition (SVD) has been applied to the half axes of each ellipsoid.
Results

- $I_C a, C_b$ can be optimized for different purposes by weighting the cost function differently:

  JND-uniformity vs. hue-linearity
Results

- $I_{C_a}C_b$ can be optimized for different purposes by weighting the cost function differently:

JND-uniformity vs. hue-linearity
ICₐCₜ compared to YCₜCₜₚ

- Better JND uniformity / encoding efficiency (YCbCr JNDs can range from half a 10bitCV to more than one hundred 10bitCVs)
- More tonal resolution around pastels
$IC_aC_b$ compared to $YC_bC_r$

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IC<sub>a</sub>C<sub>b</sub> compared to YC<sub>b</sub>C<sub>r</sub>

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- More tonal resolution around pastels
- Better hue-linearity
- Better iso-luminance
$IC_a C_b$ compared to CIE 1976 $u'v'$ based encodings

- More perceptually uniform
- More tonal resolution around skin tones
IC\textsubscript{a}C\textsubscript{b} compared to CIE 1976u’v’ based encodings

- More perceptually uniform
- More tonal resolution around skin tones
- Better hue-linearity

![Graphs showing comparison of IC\textsubscript{a}C\textsubscript{b} and CIE 1976u’v’ encodings](Hung & Berns Hue-Linearity (@100cd/m\textsuperscript{2}))
IC_aC_b compared to CIE 1976u’v’ based encodings

- More perceptually uniform
- More tonal resolution around skin tones
- Better hue-linearity
- Smoother modeling of the Hunt effect
IC<sub>a</sub>C<sub>b</sub> compared to CIE 1976u′v′ based encodings

- More perceptually uniform
- More tonal resolution around skin tones
- Better hue-linearity
- Smoother modeling of the Hunt effect
- Less computations needed (no division)
Further research

- Optimization sometimes has to be run multiple times to find global minima when initializing $x_0$ with random values from the full range of possible values.

- Example local minima:

  - Can be easily excluded by running optimization multiple times
Further research

- Test set data was small
  - $N = 2$ to 30 depending on the data set.

- Acquisition methods for the test sets could be enhanced
  - Method of adjustment for JNDs suboptimal

- Running the optimization on the verification set instead of the test set resulted in a stronger compression of the blue-yellow axis
Conclusion

- We present a new HDR color encoding that performs better in coding efficiency compared to current approaches:
  - $Y'C_bC_r$ PQ
  - $Y'C_bC_r$ BBC
  - $Y''u''v''$

- Our color space is co-optimized for encoding efficiency and color volume mapping (Tone Mapping & Gamut Mapping) and is therefore applicable for HDR and WCG color encoding in TV and cinema scenarios.
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References


