



CIC 31 .COLOR & . imaging CONFERENCE

Color Science and Engineering Systems, Technologies, and Applications

FINAL PROGRAM AND PROCEEDINGS



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IS&T: Society for Imaging Science and Technology
7003 Kilworth Lane
Springfield, VA 22151 USA
703/642-9090; 703/642-9094 fax
info@imaging.org
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BIENVENUE A CIC31!

This year we are returning to Europe, specifically Paris. In our suitcase we have an interesting program for you, including short courses, workshops, keynote talks, and technical sessions that highlight the dynamic nature of our color science community.

As CIC27 General Chair Nicolas Bonnier wrote in his 2019 introduction to the proceedings, I am also very pleased to welcome you to my hometown and the campus where I did my undergraduate and master's studies in image processing. A final project in multi-colorants printing for my Master's degree was my entree to the world of color science and CIC—and I haven't looked back.

I've attended every CIC but one since CIC18 in 2010, and have participated in all the stages of the event, starting with a paper being rejected from my PhD student time to eventually succeeding in publishing an article with great pride. My feelings and involvement regarding this conference have never diminished. I started my service as a reviewer and have pretty much served in all the roles of the conference committee. I am pleased to serve as this year's general chair, and in debt to the amazing team I've had the pleasure to work with preparing for our week in France.

CIC31 begins with our classic and intensive one-day introduction course to color science, along with courses on cameras, gamuts, and deep/machine learning, a workshop on color grading for digital cinema, and the full-day, collocated, material appearance workshop organized by GDR APPAMAT with a special session on cosmetics and facial appearance. Day two is dedicated to more short courses and workshops, from light, HDR, displays, and advanced color to cultural heritage and image quality. Needless to say, there is always something to learn when taking a short course or participating in a workshop given by specialists in the field.

Wednesday to Friday encompass the core of the technical conference. Technical Program Chairs Javier Vazquez Corral and Carol Payne have organized eight sessions of 32 oral and 22 interactive poster presentations. The program is enlivened by three keynotes and an invited talk:

- Dr. Michael J. Murdoch (RIT), "Mastering Light: Reproduction, Reality, and Augmentation"
- Dr. Sira Ferradans (DXOMARK), "On Evaluating Skin Color User Preferences for Smartphone Photography"
- Daniele Siragusano (FilmLight), "Colour Science vs. Colour Engineering in High-End Motion Picture"
- Anthony Pamart (CNRS), "Upraising Challenges of 3D Digitization Strategies in the Framework of the Notre-Dame de Paris Scientific Worksite"

Finally, we look forward to the welcome and conference receptions and a robust social program—including a photography contest—allowing us time to connect with colleagues who have become friends and meet new colleagues with whom friendship is sure to grow.

I look forward to talking with you in Paris and wish everyone a great conference!

—Jeremie Gerhardt
CIC31 General Chair

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COURSE AND WORKSHOP PROGRAM



MONDAY 13 NOVEMBER 2023

8:00 – 17:45

SHORT COURSES

SC01: Color and Imaging

Instructor: Gaurav Sharma, University of Rochester

SC02: Objective and Repeatable Color Capture in Scattering Media

Instructors: Derya Akkaynak and Grigory Solomatov, University of Haifa & Interuniversity Institute of Marine Sciences in Eilat

SC03: Color Gamut Mapping

Instructor: Ján Morovic, HP Inc.

9:00 – 17:45

APPAMAT/IS&T INTERNATIONAL WORKSHOP ON MATERIAL APPEARANCE

ORGANIZED BY GDR APPAMAT



9:00 | **Welcome and Introduction**, Mathieu Hébert (GDR Appamat), Suzanne Grinnan (IS&T)

9:05 | **Keynote** | Microstructure-appearance relationship in historical pigment, Victor Gonzalez, CNRS, PPSM, ENS Paris-Saclay, France

9:40 | Appearance Measurement and Modeling

Meso-facets for goniochromatic 3D printing, Lubna Abu Rmaileh, Fraunhofer IGD, Germany

High dynamic range merging algorithms for traceable luminance imaging, Alice Dupiau, CNAM, France

In-situ and highly portable SVBRDF acquisition method, Corentin Cou, INRIA Bordeaux, France

A pilot color matching experiment between an LCD and OLED display, Pooshpanjan Roy Biswas, ENTPE, France

10:20 | Coffee

10:50 | **Keynote** | Human face complexion in paintings, Laurence Tardy, Ecole du Louvre, France

11:10 | Cultural Heritage Materials

Recovering lost polychromy: Digital reconstruction of ancient Roman sculptures, Yoko Arteaga, NTNU, Norway

How can one detect changes of appearance during the process of conservation?, Emma Gillet, Museum National d'Histoire Naturelle, France

Exploring the optical properties of the stained glass windows in Conques Abbey by Pierre Soulages, Vanina Ambias and Alexandre Bebon, Institut d'Optique Graduate School, France

The Scream (ca. 1910) through the years: From photographic documentation to digital rejuvenation, Irina Ciortan, NTNU, Norway

Enhancing the calibration work-flow for UV imaging, Chloé Bernard, Institut national du patrimoine, France

12:00 | Visual Attributes

Exploration of core material appearance features, Jirí Filip, Czech Academy of Sciences, Czech Republic

Can we control perceived translucency using spatial augmented reality?, Davit Gigilashvili, NTNU, Norway

Interactive exploration of iridescence using rough Bragg, Gary Fourneau, INRIA Bordeaux, France

Simulation and evaluation of sunglass colour vision, Sophie Jost, ENTPE, France

12:30 | Poster session

14:00 | **Keynote** | Photonic pigments for cosmetics, Kevin Vynck, CNRS, ILM, France

14:30 | Metrology for Cosmetics

Physically-based modeling of the colored appearance of foundations, Loïc Tran, L'Oréal, France

Edge-loss effect in skin reflectance measurements, Lou Gevaux, CNAM, France

Lip color measurement: A new hyperspectral imaging, Héroïse Vergnaud, LVMH Recherche, France

Colour difference threshold for 3D facial images, Ruili He, University of Leeds, UK

15:10 | **Keynote** | Facial appearance measurement, Kaida Xiao, School of Design, University of Leeds, UK

15:45 | Coffee

16:20 | Digital Methods for Cosmetics

Multiscale journey from a digital product design to real life photoprotection cosmetics, Maria Ortiz Segovia, L'Oréal, France

Developing inclusive cosmetics ranges for multicultural consumers, Theo Phan Van Song, L'Oréal, France

A neural approach for spectral reconstruction of facial RGB images, Fereshteh Mirjalili, NTNU, Norway

DigitHair: 3D hair rendering engine for hair coloration, Hui Ding, L'Oréal, France

Cosmetics and beauty in the everyday, Nicole Hall, Institut d'Optique Graduate School, France

17:10 | **Keynote** | Facial appearance assessment, Yoko Mizokami, Chiba University, Japan

10:00 – 14:00 WORKSHOP

W1: Color Grading for Digital Cinema

Conveners and Speakers: Charles Poynton, independent researcher, and Laurens Orij, Crabsalad

TUESDAY 14 NOVEMBER 2023

8:00 – 15:30

SHORT COURSES

SC05: Camera Color Characterization: Theory and Practice

Instructors: Dietmar Wueller, Image Engineering GmbH & Co. Kg, and Eric Walowitz, consultant

SC06: Material Appearance Measurement and Characterization

Instructor: Yoko Arteaga, Norwegian University of Science and Technology (NTNU)

SC07: Vivid Luminescence: Mastering Color & Color Rendition in LED Lighting

Instructor: Michael Murdoch, Rochester Institute of Technology

SC08: Advanced Colorimetry and Color Appearance

Instructor: Gaurav Sharma, University of Rochester

SC09: Color Image Analysis with Deep Learning: Techniques and Best Practices

Instructors: Ahmed Mohammed, SINTEF and NTNU, and Marius Pedersen, NTNU

SC10: High-Dynamic-Range (HDR) Theory and Technology

Instructor: Alessandro Rizzi, Università degli Studi di Milano

SC12: Color Imaging Challenges in AR VR and MR Imaging Systems

Instructor: Kevin J. Matherson, Microsoft

SC13: Deep Learning for Color

Instructors: Simone Bianco and Marco Buzzelli, University of Milano-Bicocca

SC14: High Dynamic Range Imaging and Display - Technologies, Applications, and Perceptual Considerations

Instructor: Timo Kunkel, Dolby Laboratories, Inc.

SC15: Color Spaces Research and Applications

Instructor: Ming Ronnier Luo, Zhejiang University

15:45 – 18:00

WORKSHOPS

W2: Challenges in Image Quality Assessment

Conveners: Marius Pedersen, Colourlab director and professor, and Seyed Ali Amirshahi, associate professor, NTNU (Norway)

Confirmed speakers:

- Azeddine Beghdadi, University Sorbonne Paris Nord (France)
- Simon Hviid Del Pin, NTNU (Norway)
- Chaker Larabi, Université de Poitiers (France)
- Dietmar Saupe, Universität Konstanz (Germany)
- François-Xavier Thomas, DxOMark (France)
- Sophie Triantaphillidou, University of Westminster (UK)

W3: Material Appearance Measurement and Reproduction for Cultural Heritage Applications

Convener Yoko Arteaga, and Moderator Jon Yngve Hardeberg, NTNU (Norway)

Confirmed speakers:

- Yoko Arteaga, NTNU (Norway)
- Clotilde Boust, C2RMF (France)
- Stephanie Courtier, C2RMF (France)
- Christophe Leynadier, Mihaly Group (France)

W4: Display Simulation Pipeline for Augmented Reality (AR)

Convener and Speaker: Christopher Reidy, Meta Platforms, Inc. (US)

17:30 – 18:45

WELCOME RECEPTION

Join colleagues in the CICSU Auditorium Foyer for wine and canapés to kick off the week.



TECHNICAL PROGRAM: SCHEDULE AND ABSTRACTS

WEDNESDAY 15 NOVEMBER 2023

WELCOME AND OPENING KEYNOTE

Session Chair: Jérémie Gerhardt, DNEG (Canada)

9:00 – 10:00

Mastering Light: Reproduction, Reality, and Augmentation,

Michael J. Murdoch, Rochester Institute of Technology (US) *

As we gather in the City of Light, consider that everything visible is light. We, color and imaging scientists and practitioners, are masters of light, reproducing light through imaging, creating and utilizing light in our real environment, and augmenting our illuminated reality with advanced displays and optics. Imaging, a core topic of CIC, is about the reproduction of light, which is foremost a question of tone and color reproduction, and we develop and master technologies from reflective pigments to emissive displays. Reality itself is rendered and sensed with light, and as we choose to light our environment with LED illumination, color rendition is a central question for visual quality. Reality and imaging converge in augmented reality—AR—which can insert interactive imagery into our illuminated world. In AR, this mix of real and augmented reveals important questions about adaptation and color perception. Mastering light in real and augmented reality incorporates the newest, evolving technologies, while we rely on the foundations of our predecessors: both the intuitive artists whose paintings we still admire, and the rational scientists whose findings we still trust.

IMAGE PERCEPTION EXPERIMENTS

Session Chair: Davit Gigivalishi, NTNU (Norway)

10:00 – 12:20

10:00 **Perceived Color of Binocular Hue Mixture under Different Background Luminance Levels**, Dingyu Hu, Shining Ma, Yue Liu, Yonglian Wang, and Weitao Song, Beijing Institute of Technology (China) 1

Three-dimensional (3D) displays employ the technique of binocular disparity, by presenting two separate images with parallax cues to the two eyes, resulting in the perception of stereo vision. The human brain can fuse these two images into a single stereoscopic image, provided that their color difference falls within the fusion limit. Prior research on binocular color fusion has mostly concentrated on assessing the fusion limit across different conditions, but limited attention has been given to investigating binocular color mixture, particularly concerning opposite color pairs. In order to explore the impact of background luminance on the binocular mixture of opposite colors, a series of color matching experiments were conducted for three background luminance levels using a custom-built stereoscopic display. The findings reveal that as the contrast of the background luminance decreases, the binocular color mixture is more affected by the sensory dominant eye.

10:20 **A Study of Spatial Chromatic Contrast Sensitivity based on Different Colors, Luminance, and Stimulus Patterns**, Ruihan Tang, Qiang Xu, and Ming Ronnier Luo, Zhejiang University (China) . 7

The goals of this work are to accumulate experimental data on contrast sensitivity functions and to establish a visual model that incorporates

spatial frequency dependence. In the experimental design, two patterns were compared: fixed-size and fixed-cycle stimuli from different luminance levels. The detection thresholds have been measured for chromatic contrast patterns at different spatial frequencies. The present experiment was conducted with the aim to form a most comprehensive data by combining with our data. The experimental parameters including (1) five colour centres (white, red, yellow, green, and blue), which were recommended by the International Commission on Illumination (CIE), at two different luminance levels for each colour centre; (2) three colour directions for each colour centre, namely luminance, red-green, and yellow-blue and (3) five spatial frequencies, 0.06, 0.24, 0.96, 3.84, and 6.00 cycles per degree (cpd). The present and our earlier data were combined to form a complete set data to develop and test different models. A 10-bit display characterized by GOG model was used to obtain contrast thresholds of different color centers by the 2-alternative forced choice method and stair-case method. The experimental results revealed different parametric effects and also confirmed the McCann's finding that the number of cycles affects the comparative sensitivity. Finally, a cone contrast model and a postreceptoral contrast model proposed by Mantiuk et al was developed by fitting the visual test data (fixed number of cycles and fixed size). The models could accurately predict the contrast sensitivity of different color centers, spatial frequencies and stimulus.

10:40 – 11:20 COFFEE BREAK AND EXHIBIT

11:20 **High-dynamic-range Colour Appearance Data to Verify CAM16-UCS**, Xinye Shi, Yuechen Zhu, and Ming Ronnier Luo, Zhejiang University (China) 13

The purpose of this study is to accumulate colour appearance data under high dynamic luminance range. Two experiments were conducted based on different types of stimuli, colour patches and colour images. The colour patch experiment was conducted to match corresponding data between colors on a display and the real scene viewed under high dynamic range viewing conditions. Ten observers assessed 13 stimuli under 6 illuminance levels ranged from 15, 100, 1000, 3160, 10,000 to 32000 lux. Observers adjusted the color patches on a display screen to match the color samples of the real scene against of a neutral background (The reflectivity was 35%). The visual results showed a clear trend, an increase of illuminance level raised vividness perception (both increases in lightness and colorfulness). However, CAM16-UCS did not give accurate prediction to the visual results, especially in the lightness direction. The model was then refined to achieve satisfactory performance and to truthfully reflect the visual phenomena. By modifying the lightness induction factor in calculating lightness according to adaptive luminance, the predictions of the model and the visual results had a good agreement in the direction of colour shift. The colour image experiment was carried out using 3 images assessed by 10 observers to test the CAM16-UCS on image generation. The results showed the modified model based on patches do not perform well and a further modification was made to come out a modified CAM16-UCS for images.

*No proceedings paper associated with talk.

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11:40 **The Age Effect on Observer Colour Matching and Individual Colour Matching Functions**, Keyu Shi¹, Ming Ronnier Luo¹, Andrew Rider², and Andrew Stockman^{1,2}; ¹Zhejiang University (China) and ²University College London (UK) **20**

The visual changes caused by aging have an important effect on human vision. In this study, a series of color matching experiments were conducted to explore the differences in color matching results between observers of different age groups. The experiments were conducted using a visual trichromator, which could be illuminated by 18 LEDs with different peak wavelengths as light sources that formed 11 different triplets of RGB primaries. The matched and reference fields observed by the observers in the experiment were equally sized semicircular fields that together formed a circular field. A fixed triplet of RGB primaries produced the white reference field on the right side. It was matched on the left-side by adjusting the primary intensities of each of the 11 triplets of RGB primaries. The white reference stimulus was fixed at 120 cd/m² luminance level. One hundred Chinese observers with normal colour vision were divided by decades into 7 groups from 10 to 80 years old. The matches were analysed to estimate their cone spectral sensitivities and photopigment, macular and lens optical densities. The experimental results show relatively little variability with age, except as expected increases in lens density with age, and older observers showed more inter-observer variability. The analysis suggests that some of the mean colour matching parameters assumed by the CIE, such as the macular pigment optical density, do not apply for these observers.

12:00 **The Perceptibility of Color Differences in Continuous Transitions**, Jan Morovic, HP Inc. (UK), and Peter Morovic, HP Inc. (Spain) . . **26**

Whether two stimuli appear to be of different colors depends on a host of factors, ranging from the observer, via viewing conditions to content and context. Previously, studies have explored just noticeable difference thresholds for uniform colors viewed with or without spatial separation, for complex images and for fine features like lines in architectural drawings. An important case that has not been characterized to date is that of continuous color transitions, such as those obtained when selecting two colors and generating a sequence of intermediate colors between them. Such transitions are often part of natural scenes (e.g., sunsets, the sky, curved surfaces, soft shadows, etc.) and are also commonly used in visual design, including for backgrounds and various graphical elements. Where the just noticeable difference lies in this case will be explored here by way of a small-scale, pilot experiment, conducted in an uncontrolled, on-line way. Its results suggest a threshold in the region of 0.5 to 0.8 ΔE_{2000} for the few stimuli evaluated in the pilot experiment reported here and indicate a behavior that is in the region of viewing solid colors without a gap. A pilot verification with complex images also showed thresholds with a comparable range.

3-MINUTE EXHIBITOR PREVIEWS

Session Chair: Jérémie Gerhardt, DNEG (Canada)

12:20 – 12:30

Learn more about this year's exhibitors: Image Engineering, Thousand Lights Lighting, and TeleLumen

12:30 – 14:00 LUNCH ON OWN

COLOR CONSTANCY I

Session Chair: Lili Zhang, Meta Reality Labs (US)

14:00 – 15:00

14:00 **JIST-First Locus Filters: Theory and Application**, Rada Deeb, Graham D. Finlayson, and Elaheh Daneshvar, University of East Anglia (UK). **see JIST 67(5)/**
DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050407

Recently, a theoretical framework was presented for designing colored filters called Locus Filters. Locus filters are designed so that any Wien-Planckian light, post filtering, is mapped to another Wien-Planckian light. Moreover, it was also shown that only filters designed according to the locus filter framework have this locus-to-locus mapping property. In this paper, we investigate how locus filters work in the real world. We make two main contributions. First, for daylight, we introduce a new daylight locus with respect to which a locus filter always maps a daylight to another daylight (and their correlated color temperature maps in analogy to the Wien-Planckian temperatures). Importantly, we show that our new locus is close to the standard daylight locus (but has a simpler and more elegant formalism). Secondly, we evaluate the extent to which some commercially available light balancing and color correction filters behave like locus filters.

14:20 **RGB Illuminant Compensation using Spectral Super-resolution and Weighted Spectral Color Correction**, Marco Buzzelli¹, Mikhail K. Tchobanov², Raimondo Schettini¹, and Simone Bianco¹; ¹University of Milano - Bicocca (Italy) and ²Huawei Technologies Co. Ltd. (Russia) **33**

This paper presents a novel approach for spectral illuminant correction in smartphone imaging systems, aiming to improve color accuracy and enhance image quality. The methods introduced include Spectral Super Resolution and Weighted Spectral Color Correction (W-SCC). These techniques leverage the spectral information of both the image and the illuminant to perform effective color correction. Experimental evaluations were conducted using a dataset of 100 synthetic images, whose acquisition is simulated using the transmittance information of a Huawei P50 smartphone camera sensor and an Ambient light Multispectral Sensor (AMS). The results demonstrate the superiority of the proposed methods compared to traditional trichromatic pipelines, achieving significant reductions in colorimetric errors measured in terms of ΔE_{94} units. The W-SCC technique, in particular, incorporates per-wavelength weight optimization, further enhancing the accuracy of spectral illuminant correction. The presented approaches have valuable applications in various fields, including color analysis, computer vision, and image processing. Future research directions may involve exploring additional optimization techniques and incorporating advanced machine learning algorithms to further advance spectral illuminant correction in smartphone imaging systems.

14:40 **JIST-First Color Correction of Mars Images: A Study of Illumination Discrimination Along Solight Locus**, Emilie Robert^{1,2,3}, Che Shen³, Magali Estriebeau², Edoardo Cucchetti¹, and Mark Fairchild³; ¹Centre National d'Etudes Spatiales (France), ²ISAE-SUPAERO (France), and ³Rochester Institute of Technology (US) **see JIST 67(5)/**
DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050410

Geologists consider it crucial to work on faithful images of Mars. However, no color correction is yet done systematically on those images, especially due to the poor knowledge of the local martian weather. The weather is highly fluctuating and with the low gravity of the planet, it tends

to set the conditions for varying amounts of dust in the atmosphere and ground illumination variations as well. Low discrimination of light variations by the Human Visual System is explained by Chromatic Adaptation (CA). Color images processing therefore often accounts for a step related to CA. This study investigates whether this step has to be applied to Mars images as well and is done through an illumination discrimination task performed on 15 observers for stimuli along daylight locus and solight locus (lights of Mars planet) generated through a 7-LEDs lighting system. This study gives outputs in agreement with other on daylight locus while showing low differences between results under daylight and solight.

TWO-MINUTE INTERACTIVE PAPER PREVIEWS I

Session Chair: Luke Hellwig, Samsung (US)

15:00 – 15:30

Development and Testing of Vividness and Depth Model based on Different Scale Combination, Molin Li and Ming Ronnier Luo, Zhejiang University (China)

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Vividness and Depth are widely used in image and textile industry. And these scales were derived from one-dimensional scales of CIELAB L^* and C^*_{ab} . However, these scales are limited to relative scales with a reference white, which makes it difficult for them to adapt to the variation in the world. This paper has introduced an experiment that focuses on assessing the wide range of luminance levels in a visual context, ranging from 10 cd/m² to 10000 cd/m². The experiment employed a method called magnitude estimation to gauge the perception of Vividness, Depth, Whiteness, and Blackness scales. The judgments were obtained through 10 observer x 40 NCS Sample x 4 lux level x 4 scales x 1.1 (10% repeat set), resulting in a total of 7040 assessments. This article mainly introduces the development of vividness and depth scales using combinations of relative scales, absolute scales, and the mixture scales like CAM16-UCS.

Improve Image White Balance by Facial Skin Color, Liqing Wang¹, Yuechen Zhu¹, Xiaoxuan Liu¹, and Ming Ronnier Luo^{1,2}; ¹Zhejiang University (China) and ²University of Leeds (UK)

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In area of white balance, the process of large colored background images seems to be a problem. Regarding this issue, a white balance algorithm based on facial skin color was proposed. A neural network-based object detection algorithm and an adaptive threshold segmentation algorithm were combined to achieve the accurate segmentation of skin color pixels. Then a 3-dimension color gamut mapping method in CIELAB color space was used to do the illumination estimation. Last, CAT16 model was applied to rendering the images to standard lighting condition. Besides, an ill white balanced images dataset taken against large colored backgrounds were prepared to test the present algorithm and others' performance. The results show the proposed algorithm performs better on the dataset.

Color-temperature Cross-modal Association: The Relationships of Hue, Saturation, and Brightness with Temperature, Weiran Cui and Sunao Iwaki, University of Tsukuba and National Institute of Advanced Industrial Science and Technology (AIST) (Japan)

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The cross-modal association is a specific connection experienced between stimuli, attributes, or perceptual dimensions. Most previous studies related to the cross-modal association of color and temperature use subjective report methods, and the underlying mechanisms behind this association are unclear. This study used the Implicit Association Test (IAT) paradigm combined with event-related potentials (ERPs) elicited by color stimuli to explore the cross-modal association between color, in terms of hue, satu-

ration, and brightness, and temperature. Cross-modal associations between hue and temperature, as well as saturation and temperature were found. There was no evidence for the existence of a brightness-temperature cross-modal association. Additionally, significant differences in the average N1 amplitudes were observed in the hue IAT task. Significant differences in the average N2 and N400 amplitudes were observed in both the hue and saturation IAT tasks, indicating that both corresponding cross-modal associations have a semantic basis to some degree.

A Psychological Study: Importance of Contrast and Luminance in Color to Grayscale Mapping, Prasoon Ambalathankandy, Yafei Ou, Sae Kaneko, and Masayuki Ikebe, Hokkaido University (Japan)

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Grayscale images are essential in image processing and computer vision tasks. They effectively emphasize luminance and contrast, highlighting important visual features, while also being easily compatible with other algorithms. Moreover, their simplified representation makes them efficient for storage and transmission purposes. While preserving contrast is important for maintaining visual quality, other factors such as preserving information relevant to the specific application or task at hand may be more critical for achieving optimal performance. To evaluate and compare different decolorization algorithms, we designed a psychological experiment. During the experiment, participants were instructed to imagine color images in a hypothetical "colorless world" and select the grayscale image that best resembled their mental visualization. We conducted a comparison between two types of algorithms: (i) perceptual-based simple color space conversion algorithms, and (ii) spatial contrast-based algorithms, including iteration-based methods. Our experimental findings indicate that CIELAB exhibited superior performance on average, providing further evidence for the effectiveness of perception-based decolorization algorithms. On the other hand, the spatial contrast-based algorithms showed relatively poorer performance, possibly due to factors such as DC-offset and artificial contrast generation. However, these algorithms demonstrated shorter selection times. Notably, no single algorithm consistently outperformed the others across all test images. In this paper, we will delve into a comprehensive discussion on the significance of contrast and luminance in color-to-grayscale mapping based on our experimental results and analysis.

Metrology-driven Image Synthesis for Quality Control, Meldrick Reimmer, Hermine Chatoux, and Olivier Aubreton, Université de Bourgogne (France)

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Metrology plays a critical role in the rapid progress of Artificial Intelligence (AI), particularly in computer vision. This article explores the importance of metrology in image synthesis for computer vision tasks, with a particular focus on object detection for quality control. The aim is to improve the accuracy, reliability and quality of AI models. Through the use of precise measurements, standards and calibration techniques, a carefully constructed dataset has been generated and used to train AI models. By incorporating metrology into AI models, we aim at improving their overall performance and robustness.

Optimised Spherical Sampling of the Object Colour Solid, Hans J. Rivertz, Norwegian University of Science and Technology (Norway), and Michal Mackiewicz, University of East Anglia (UK)

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We propose a new method for approximating object colour solids, which we call Optimised Spherical Sampling. We compare our new method to the previously described methods based on 1) the two-transition conjecture of Schrodinger and 2) Random Spherical Sampling. The proposed method is based on the approximation of the OCS local error at every face of the volume and its subsequent optimisation. We find that the new method produces a significantly less error for the same number of samples than the two prior art methods.



Color Analysis and Color Management in Mass Digitization of Transparencies at the National Digital Archives in Poland, Mateusz

Bolesta, *The National Digital Archives (Poland)*. **74**
Professional digitization of cultural heritage items in the Polish State Archives can be divided into two major branches: digital imaging of transparencies and reflectives. While the latter has been meticulously standardized in accordance with ISO 19264 and domestic guidelines, the case is much different for the former. This paper is aimed at addressing the issue of color in mass digitization projects.

JST-First An Appearance Reproduction Framework for Printed 3D Surfaces, Tanzima Habib, Phil Green, and Peter Nussbaum, Norwegian University of Science and Technology (Norway) see JIST 67(5)/DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050413

Bidirectional reflection distribution function (BRDF) is used to measure colour with gloss and surface geometry. In this paper, we aim to provide a practical way of reproducing the appearance of a 3D printed surface in 2.5D printing of any slope angle and colour in a colour-managed workflow as a means for softproofing. To account for the change in colour due to a change in surface slope, we developed a BRDF interpolation algorithm that adjusts the colour of the tristimulus values of the flat target to predict the corresponding colour on a surface with a slope. These adjusted colours are then used by the interpolated BRDF workflow to finally predict the colour parameters for each pixel with a particular slope. The effectiveness of this algorithm in reducing colour differences in 2.5D printing has been successfully demonstrated. We then finally show how all the components, slope colour adjustment method, interpolated BRDF parameters algorithm, and BRDF model encoded profiles using iccMAX are connected to make a practical appearance reproduction framework for 2.5D printing.

JST-First Acquisition of Color Reproduction Technique based on Deep Learning using a Database of Color-converted Images in the Printing Industry, Ikumi Hirose¹, Ryosuke Yabe¹, Toshiyuki Inoue², Koushi Hashimoto³, Yoshikatsu Arizono², Kazunori Harada³, Vinh-Tiep Nguyen^{4,5}, Thanh Duc Ngo^{4,5}, Duy-Dinh Le^{4,5}, and Norimichi Tsumura¹; ¹Chiba University (Japan), ²Sanko Corporation (Japan), ³Nikko Process Corporation (Japan), ⁴University of Information Technology (Vietnam), and ⁵Vietnam National University (Vietnam). see JIST 67(5)/DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050402

Color-space conversion technology is important to output accurate colors on different devices. In particular, CMYK (Cyan, Magenta, Yellow, and Key plate) used by printers has a limited range of representable colors compared with RGB (Red, Green, and Blue) used for normal images. This leads to the problem of loss of color information when printing. When an RGB image captured by a camera is printed as is, colors outside the CMYK gamut are degraded, and colors that differ significantly from the actual image may be output. Therefore, printers and other companies manually correct color tones before printing. This process is based on empirical know-how and human sensitivity and has not yet been automated by machines. Therefore, this study aims to automate color correction in color-space conversion from RGB to CMYK. Specifically, we use machine learning, utilising a large color-conversion database owned by printing companies, which has been cultivated through past correction work, to learn the color-correction techniques of skilled workers. This reduces the burden on the part of the work that has been done manually, and leads to increased efficiency. In addition, the machine can compensate for some of the empirical know-how, which is expected to simplify the transfer of skills. Quantitative and qualitative evaluation results show the effectiveness of the proposed method for automatic color correction.

Usefulness of Saliency Map in Estimating Food Appearance

Favorability, Natsuko Minegishi, Konica Minolta, Inc.; Kenji Maeda, Takuo Kawajiri, and Shusuke Yamada, Nippon Heater Kiki Co., Ltd.; and Akira Hirano and Shuji Toyosumi, Shinko Glass Industry Co., Ltd. (Japan) **80**

Saliency maps are widely known as a model for simulating visual attention and are also used in industry. They basically indicate whether target images have features that perceived, which predicts the region on which people's eyes focus. However, the saliency may also be related to the favorability perceived by observers. Our goal examined if the saliency of the food product estimates the favorability. Specifically, we manipulated the saliency of hot snacks through the display case design and examined how the evaluation of favorability (the degree of tasty looking) changed. We expected that if we could estimate the favorability of the target product by only using the saliency map, which is an image to show locations with high saliency in images, it would be very useful to estimate the variables, which correlate with the favorability of the appearance of the hot snacks in a short time. Hence, in this study, the favorability of hot snack appearances was evaluated by participants, and the correlation between the favorability score and a saliency value that we defined was analyzed. The tendency of favorability against saliency was compared with that to color conditions of lighting or background of target objects. As a result, it has been indicated that there was the correlation between favorability of food appearance and saliency. Therefore, the possibility that the saliency map can be used as a tool to estimate favorability has been supported.

Overview of Spectral Sensitivity Estimation Without a Camera, Grigory Solomatov and Derya Akkaynak, Haifa University (Israel) A-1

Consumer digital cameras are not tools designed for scientific imaging, i.e., they are not scientific light-measuring devices. Yet their outputs—digital photos and videos—constitute major sources of data for image processing, colorimetry, computational photography, computer vision, and machine learning. Typically, research utilizing consumer camera imagery focuses on the development of filters or algorithms that alter the visual appearance of images, or on the understanding of scene content and structure with downstream goals like recognizing, tracking, or counting objects. For many of these goals, successfully recovering scene reflectance and/or illumination is key (and often the main goal itself), but these tasks are complicated by the fact that consumer cameras do not capture colors in a standardized way.

What Underlies Focal Colours?, Brian Funt and Emtis Roshan, Simon Fraser University (Canada) 86

Colour names are generally attributed to specific colour categories, of which the most representative colour is termed a focal colour. The question as to what underlies this categorization is addressed in this paper. Are the categories simply a naming convention of colours with a specific 'perceptual salience?' Results based on the wraparound Gaussian model of reflectances show that colour categories follow naturally from a perception-agnostic segmentation of colours defined in this space. In other words, a segmentation based only on colour coordinates, not perceived colours. Furthermore, it is demonstrated that the concept of a focal colour can be explained as a colour that is both (i) representative of a colour category, and (ii) relatively stable under a wide range of illuminant spectra without depending upon chromatic adaptation.

15:30 – 16:10 COFFEE BREAK AND EXHIBIT

COLOR CONSTANCY II

Session Chair: Emilie Robert, CNES (France)

16:10 – 17:30

- 16:10 **JIST-first Grey Balance in Cross Media Reproductions**, Gregory High, Peter Nussbaum, and Phil Green, Norwegian University of Science and Technology (Norway) see JIST 67(5)/DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050411

Grey balance plays an important role in determining the device values needed to reproduce colours which appear achromatic throughout the tonal range. However, complete observer adaptation to the media white rarely occurs, and these designated device values can still appear non-neutral. This poses a problem for cross-media reproductions, where a mismatch in neutral colours is often the most noticeable difference between them. This paper presents two related experiments which investigate a means of gaining better visual agreement between reproductions which have different background colours or media whites. The first quantifies the degree of adjustment (the degree of media relative transform) needed to make an appearance match between grey patches on a white background and on background colours of various hues and colourfulness. It was found that the degree of adjustment was near-linearly related to the luminance of the patch itself, with lighter patches requiring greater adjustment towards the background colour. Neither the hue nor the chroma of the patch's background had any significant effect on the underlying function. In the second experiment, this concept is applied to pictorial images on paper-coloured backgrounds. Three pixelwise rendering strategies were compared. In side-by-side viewing, the adaptive control of neutrals outperformed the media relative transform in all cases. Even for modest differences in paper colour (ΔE_{ab} of 3), images with significant neutral content benefited from the adaptive approach.

- 16:30 **Learning Color Constancy: 30 Years Later**, Marco Buzzelli, Raimondo Schettini, and Simone Bianco, University of Milano - Bicocca (Italy) 91

The first paper investigating the use of machine learning to learn the relationship between an image of a scene and the color of the scene illuminant was published by Funt et al. in 1996. Specifically, they investigated if such a relationship could be learned by a neural network. During the last 30 years we have witnessed a remarkable series of advancements in machine learning, and in particular deep learning approaches based on artificial neural networks. In this paper we want to update the method by Funt et al. by including recent techniques introduced to train deep neural networks. Experimental results on a standard dataset show how the updated version can improve the median angular error in illuminant estimation by almost 51% with respect to its original formulation, even outperforming recent illuminant estimation methods.

- 16:50 **Practical Cross-sensor Color Constancy using a Dual-mapping Strategy**, Shuwei Yue and Minchen Wei, The Hong Kong Polytechnic University (Hong Kong) 96

Deep Neural Networks (DNNs) have been widely used for illumination estimation, which is time-consuming and requires sensor-specific data collection. Our proposed method uses a dual-mapping strategy and only requires a simple white point from a test sensor under a D65 condition. This allows us to derive a mapping matrix, enabling the reconstructions

of image data and illuminants. In the second mapping phase, we transform the reconstructed image data into sparse features, which are then optimized with a lightweight multi-layer perceptron (MLP) model using the re-constructed illuminants as ground truths. This approach effectively reduces sensor discrepancies and delivers performance on par with leading cross-sensor methods. It only requires a small amount of memory (~ 0.003 MB), and takes ~ 1 hour training on an RTX3070Ti GPU. More importantly, the method can be implemented very fast, with ~ 0.3 ms and ~ 1 ms on a GPU or CPU respectively, and is not sensitive to the input image resolution. Therefore, it offers a practical solution to the great challenges of data recollection that is faced by the industry.

- 17:10 **JIST-first Visualizing Perceptual Differences in White Color Constancy**, Marco Buzzelli, University of Milano - Bicocca (Italy) see JIST 67(5)/DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050404

Algorithms for computational color constancy are usually compared in terms of the angular error between ground truth and estimated illuminant. Despite its wide adoption, there exists no well-defined consensus on acceptability and/or noticeability thresholds in angular errors. One of the main reasons for this lack of consensus is that angular error weighs all hues equally by performing the comparison in a non-perceptual color space, whereas the sensitivity of the human visual system is known to vary depending on the chromaticity. We therefore propose a visualization strategy that presents simultaneously the angular error (preserved due to its wide adoption in the field), and a perceptual error (to convey information about its actual perceived impact). This is achieved by exploiting the angle-retaining chromaticity diagram, which shows errors in chromaticities while encoding RGB angular distances as 2D Euclidean distances, and by embedding contour lines of perceptual color differences at standard predefined thresholds. Example applications are shown for different color constancy methods on two imaging devices.

OPTIONAL DXOMARK TOUR

Meet outside the auditorium at 17:30 to travel together.

18:00 – 21:00

Join other colleagues on a tour of the image quality labs.

DXOMARK



THURSDAY 16 NOVEMBER 2023

THURSDAY KEYNOTE

Session Chair: Javier Vázquez Corral, Universitat Autònoma de Barcelona (Spain)

9:00 – 10:00

On Evaluating Skin Color User Preferences for Smartphone Photography, Sira Ferradans, DXOMARK (France) *

Portraits are the most common use case for smartphone photography, however, producing a realistic and pleasant skin tone in real scenarios is still challenging for all. Around 20% of portraits are discarded due to bad image quality, and a photographer's edition (raw capture with a professional photographer retouch) is mostly preferred to a smartphone's, which suggests that contemporary smartphone cameras are far from solving the skin tone rendition problem.

These challenges are due to a lack of a clear user preferences target definition regarding color skin tone rendering. In literature, we find mostly studies that evaluate synthetic modifications of laboratory portraits. This talk shows that real setups are more complex to evaluate, and user preferences depend on many factors.

Producing non-homogeneous quality rendition across skin tones has become a sensitive issue, making its evaluation crucial. This talk discusses the challenges of systematically evaluating diverse skin tones in the lab using realistic mannequins, and how defining a target can pave the way to automatizing skin tone rendition evaluation with machine learning.

COMPUTATIONAL COLOR

Session Chair: Marco Buzzelli, University of Milano - Bicocca (Italy)

10:00 – 12:20

10:00 JIST-first Multi-attention Guided SKFHDRNet for HDR Video Reconstruction, Ehsan Ullah and Marius Pedersen, Norwegian University of Science and Technology; and Kjartan Sebastian Waaseth and Bernt-Erik Baltzersen, DvNor (Norway) see JIST 67(5)/ DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050409

We propose a three stage learning-based approach for High Dynamic Range (HDR) video reconstruction with alternating exposures. The first stage performs alignment of neighboring frames to the reference frame by estimating the flows between them, the second stage is composed of multi-attention modules and a pyramid cascading deformable alignment module to refine aligned features, and the final stage merges and estimates the final HDR scene using a series of dilated selective kernel fusion residual dense blocks (DSKFRDBs) to fill the over-exposed regions with details. The proposed model variants give HDR-VDP-2 values on a dynamic dataset of 79.12, 78.49, and 78.89 respectively, compared to Chen et al. ["HDR video reconstruction: A coarse-to-fine network and a real-world benchmark dataset," Proc. IEEE/CVF Int'l. Conf. on Computer Vision (IEEE, Piscataway, NJ, 2021), pp. 2502–2511] 79.09, Yan et al. ["Attention-guided network for ghost-free high dynamic range imaging," Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition (IEEE, Piscataway, NJ, 2019), pp. 1751–1760] 78.69, Kalantari et al. ["Patch-based high dynamic range video," ACM Trans. Graph. 32 (2013) 202–1] 70.36, and Kalantari et al. ["Deep HDR video from sequences with alternating exposures," Computer Graphics Forum (Wiley Online Library, 2019), Vol. 38, pp. 193–205] 77.91. We achieve better detail reproduction and alignment in over-exposed regions compared to state-of-the-art methods and with a smaller number of parameters.

*No proceedings paper associated with talk.

10:20 CIECAM16-based Tone Mapping of High Dynamic Range

Images, Imran Mehmood, Miaosen Zhou, Muhammad Usman
Khan, and Ming Ronnier Luo, Zhejiang University (China) . . . 102

A significant challenge in tone mapping is to preserve the perceptual quality of high dynamic range (HDR) images when mapping them to standard dynamic range (SDR) displays. Most of the tone mapping operators (TMOs) compress the dynamic range without considering the surround viewing conditions such as average, dim and dark, leading to the unsatisfactory perceptual quality of the tone mapped images. To address this issue, this work focuses on utilizing CIECAM16 brightness, colorfulness, and hue perceptual correlates. The proposed model compresses the perceptual brightness and transforms the colors from HDR images using CIECAM16 color adaptations under display conditions. The brightness compression parameter was modeled via a psychophysical experiment. The proposed model was evaluated using two psychophysical experimental datasets (Rochester Institute of Technology (RIT) and Zhejiang University (ZJU) datasets).

10:40-11:20 COFFEE BREAK

11:20 Robert W.G. Hunt Best Paper Award Simplifying Tone Curves for Image Enhancement, James Bennett and Graham Finlayson, University of East Anglia (UK) 108

A single tone curve which is used to globally remap the brightness of each pixel in an image is one of the simplest ways to enhance an image. Tone curves might be the result of individual user edits or from algorithmic processing including in-camera processing pipelines. The precise shape of the tone curve is not strongly constrained other than it is usually limited to increasing functions of brightness. In this paper we constrain the shape further and define a simple tone adjustment, mathematically, to be a tone curve that has either no or one inflexion point. It follows that a complex tone curve is one with more than one inflexion point, visually making the curve appear 'wiggly'. Empirically, complex tone curves do not seem to be used very often. For any given tone curve we show how the closest simple approximation can be efficiently found. We apply our approximation method to the MIT-Adobe FiveK dataset which comprises 5000 images that are manually tone-edited by 5 experts. For all 25,000 edited images—where some of the tone adjustments are complex—we find that they are all well-approximated by simple tone curve adjustments.

11:40 First-principles Approach to Image Lightness Processing, D. Andrew Rowlands and Graham D. Finlayson, University of East Anglia (UK) 115

There are a variety of computational formulations of retinex but it is the center/surround convolutional variant that is of interest to us here. In convolutional retinex, an image is filtered by a center/surround operator that is designed to mitigate the effects of shading, which in turn compresses the dynamic range. The parameters that define the shape and extent of these filters are tuned to give the "best" results. In their 1988 paper, Hurlbert & Poggio showed that the problem can be formulated as a regression, where corresponding pairs of images with and without the effects of shading are related by a center/surround convolution filter that is found by solving an optimization.

This paper starts with the observation that finding sufficiently large representative pairs of images with and without shading is difficult. This leads us to reformulate the Hurlbert & Poggio approach so that we analytically integrate over the whole sets of shadings and albedos, which

means that no sampling is required. Rather nicely, the derived filters are found in closed form and have a smooth shape, unlike the filters derived by the prior art. Experiments validate our method.

12:00 **Novel Methods of Brightness and Saturation Testing for High-dynamic-range Images**, Luke Hellwig^{1,2}, Dale Stoltzka², and Mark D. Fairchild¹; ¹Rochester Institute of Technology and ²Samsung Display American Lab (US) 122

A psychophysical experiment was conducted in which observers compared the saturation and brightness between high-dynamic-range images that had been modulated in chroma and achromatic lightness. Models of brightness which account for the Helmholtz-Kohlrausch effect include both chromatic and achromatic inputs into brightness metrics, and this experiment was an exploration of whether these metrics could be expanded to images. The observers consistently judged saturation in agreement with the predictions of our color appearance modeling. However, some unexpected results and differences between observers in their methods for judging brightness indicates that further modeling, including spatial effects of color perception, need to be included to apply our model of the Helmholtz-Kohlrausch effect to images.

TWO-MINUTE INTERACTIVE PAPER PREVIEWS II

Session Chair: Natsuko Minegishi, Konica Minolta, Inc. (Japan)

12:00 – 12:45

A Simple Fast Resource-efficient Deep Learning for Automatic Image Colorization, Tanmay Ambadkar, Pennsylvania State University (US), and Jignesh S. Bhatt, Indian Institute of Information Technology Vadodara (India) 126

Colorization of grayscale images is a severely ill-posed inverse problem among computer vision tasks. We present a novel end-to-end deep learning method for the automatic colorization of grayscale images. Past methods employ multiple deep networks, use auxiliary information, and/or are trained on massive datasets to understand the semantic transfer of colors. The proposed method is a 38-layer deep convolutional residual network that utilizes the CIELAB color space to reduce the problem's solution space. The network comprises 16 residual blocks, each with 128 convolutional filters to address the ill-posedness of colorization, followed by 4 convolutional blocks to reconstruct the image. Experiments under challenging heterogeneous scenarios and using the Imagenet, Intel, and MirFlickr datasets show significant generalization when assessed visually and against PSNR, SSIM, and PIQE. The proposed method is relatively simpler (16 million parameters), faster (15 images/sec), and resource-efficient (just 50000 training images) when compared to the state-of-the-art.

Perceived Translucency at Different Spatial Scales in Color and Grayscale Images, Aqsa Hassan and Davit Gigilashvili, Norwegian University of Science and Technology (Norway) 132

Many objects and materials in our daily lives are translucent. Translucency is an important attribute of appearance together with color, gloss, and texture. However, it remains largely unexplored whether and how these attributes impact each other. While the vast amount of literature exists about color reproduction, very little is known whether color reproduction at the same time affects perceived translucency. A substantial part of the translucency perception research is conducted on grayscale stimuli, which raises the question whether their findings can be generalized to the chromatic world we live in. A previous work showed that translucency changes when the image is converted to

grayscale. One potential explanation the authors offered was the easier recognition of familiar materials. In this work we conducted psychophysical experiments where four versions of the images of different objects were shown: cropped close-ups and full images both in color as well as grayscale. The observers had to classify materials in each image as transparent, translucent, or opaque. We hypothesized that cropping would make material identity more ambiguous, and hence, affect translucency. We observed that for some images, conversion to grayscale affects translucency, and this effect is usually stronger for cropped versions. However, this effect was not observed for some other images. Overall, the way color and cropping affect translucency was not systematic across the dataset, which opens up additional questions for future work to explain these cross-stimuli differences.

An HDR Image Database Construction and LDR-to-HDR Mapping for Metallic Objects, Shoji Tominaga, Norwegian University of Science and Technology (Norway) and Nagano University (Japan); and Takahiko Horiuchi, Chiba University (Japan) 138

We consider a method for reconstructing the original HDR image from a single LDR image suffering from saturation for metallic objects. A deep neural network approach is adopted for directly mapping from 8-bit LDR image to an HDR image. An HDR image database is first constructed using a large number of objects with different shapes and made of various metal materials. Each captured HDR image is clipped to create a set of 8-bit LDR images. The whole pairs of HDR and LDR images are separated and used to train and test the network. Next, we design a deep CNN in the form of a deep auto-encoder architecture. The network was also equipped with skip connections to keep high image resolution. The CNN algorithm is constructed using MATLAB's machine-learning functions. The entire network consists of 32 layers and 85,900 learnable parameters. The performances of the proposed method are examined in experiments using a test image set. We also compare our method with other methods. It is confirmed that our method is significantly superior in reconstruction accuracy and the good histogram fitting.

An Optimality Property of Matrix-R Theorem, its Extension, and the Application to Hyperspectral Pan-sharpening, Yi-Tun Lin, Graham D. Finlayson, and Abdullah Kucuk, University of East Anglia (UK) 144

The Matrix-R decomposition teaches that, with respect to a set of sensors, any spectrum can be written as the sum of its fundamental metamers—in the subspace spanned by the spectral sensitivities of the camera—and a metameric black (orthogonal to the camera spectral sensitivities). In any RGB-to-spectra recovery algorithm we might expect a good spectral recovery to have the property that, when projected onto the RGB sensors, it equals the RGB from which it was estimated. Or, equivalently, the fundamental metamers of the ground-truth and algorithm-recovered spectra should be equal.

In this paper, we make this expectation more concretized and present an elementary proof that this “Matrix-R-compliance” post-processing step must always improve the RMSE (root-mean-squared error) accuracy of any RGB-to-hyperspectral recovery algorithms. Further, we consider and rework the proof for the case where the spectral data is known to live in a basis of small finite dimension. Experimental results are presented for three historic RGB-guided hyperspectral pan-sharpening algorithms. Here the algorithm input includes a high-spatial-resolution RGB image and a low-resolution hyperspectral counterpart. We show the evidence that the RMSE accuracy of all tested algorithms are improved by this Matrix-R-compliant process, while we also find the best recovery results from adopting a low-dimensional linear model that models the variation of spectra in a scene.



Forward and Inverse Colour Calibration Models for OLED Displays,

Maliha Ashraf, Dounia Hammou, and Rafal K. Mantiuk, University of Cambridge (UK)

A-3

We compare different methods of colour calibrating OLED 4-primary displays. The forward models use different colour transformation techniques to predict device-independent tristimulus values from device native RGB values. The inverse models transform the device-dependent tristimulus values to predict the native RGB values that could produce the required colour. We found that the performance of the models depended on the display characteristics and the models that performed better in terms of forward model error were not necessarily better for inverse model performance as well.

Estimation Concentration of Pigment Component from Lip Image using Light Scattering Analysis, Ryosuke Imai¹ and Norimichi Tsumura^{1,2};

¹Chiba University and ²Hiroshima University (Japan)

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In this study, we propose a method to estimate the concentration of components of lips from RGB lip images. The lips are an essential part of the body, as their shape and color determine a person's facial expression, age, health status, and other aspects of their impression. Therefore, the lips have been of interest in cosmetology, psychology, and medicine as the subject of much research. However, only a few studies measure lip components noninvasively or analyze them histologically. Therefore, our goal is to measure the components of the lips noninvasively. We build a model for each of the vermilion regions and mucosa regions of the lip and the skin regions and discuss the differences in the concentration of the components. The results showed differences in the melanin concentration and blood volume in the skin, vermilion, and mucosa regions.

A General-purpose Pipeline for Realistic Synthetic Multispectral Image Dataset Generation, Marco Buzzelli¹, Mikhail K. Tchobanov², Raimondo Schettini¹, and Simone Bianco¹;

¹University of Milano - Bicocca (Italy) and ²Huawei Technologies Co. Ltd. (Russia).

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A pipeline for the generation of synthetic dataset of spectral scenes, with corresponding sensor readings, is here proposed. The pipeline is composed of two main parts: Part 1: Image pixel reflectance assignment. Individual pixels from an input sRGB image dataset are replaced with appropriate reflectance spectra from a given non-image reflectance dataset. The resulting dataset of reflectance images is considered the starting point for simulated sensor acquisition. Part 2: Simulated sensor acquisition. Each spectral reflectance image in the dataset is illuminated with an illuminant spectra to produce a radiance image. The resulting dataset of radiance images is then synthetically read from the simulated sensors (camera and ambient multispectral sensor) of the Huawei P50 phone, using the corresponding sensors transmittance information. The capability of generating any large-scale, diverse, and annotated synthetic spectral datasets can facilitate the development of data-driven imaging algorithms, and foster reproducible research.

A Comprehensive Image Quality Dataset to Compare No-reference and With-reference Image Quality Assessment, Nanlin Xu, Yuechen Zhu,

and Ming Ronnier Luo, Zhejiang University; and Xinchao Qu, Dajiang Innovation Technology Co., Ltd. (China)

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With the prevalence of digital devices, images are now more accessible. A method to judge the image quality of a picture and corresponding datasets are highly desired. However, previous works focused solely on total image quality, without consider image quality separately in terms of color and spatial aspects. The present study aims to fill this gap by evaluating total, color, and spatial image quality together.

The whole experiment was divided into two parts: no-reference (NR) experiment and with-reference (WR) experiment. In the NR part, 30

participants assessed total image quality (ItQ), color image quality (cIQ) and spatial image quality (sIQ) as well as their corresponding weights for color and spatial impact. In the WR part, 30 participants were asked to evaluate the difference in color and total image quality between the original image and rendered image.

Weighted IQ, obtained through linear weighting using ratio, cIQ, and sIQ, demonstrated a high correlation coefficient (0.96) with total IQ. This implies that color and spatial features of image quality can be treated as separate entities.

A no-reference image quality model was proposed to predict IQs whose accuracy of prediction obtained a correlation coefficient value of 0.80.

The Effect of An Ambient Contrast of AR (Augmented Reality) Images on Brightness Perception, Hyosun Kim, YoungJun Seo, and Yongwoo Yi, Samsung Display (South Korea)

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In an ideal AR device, only the AR object image should appear in the real environment. However, certain AR devices, such as those using a half mirror, also present the AR background surrounding the AR object due to the transmittance of the half mirror. This might be perceived as a two-dimensional display image overlapping onto the real environment. In this scenario, the perception of brightness might differ from cases where only an AR object is superimposed on the real-world background. To explore the brightness perception of AR images presented by AR glasses with half mirrors, we conducted two psychophysics experiments. In Experiment 1, using a single pair of AR glasses, we observed the brightness perception of AR images under various correlated color temperatures (CCTs) for exterior lighting. Participants perceived the AR image to be brighter than the reference image with the same luminance. The CCT of the exterior lighting had no significant effect. In Experiment 2, we investigated the effect of the AR background on the brightness perception of AR images using two pairs of AR glasses with different transmittances (35% vs. 70%). Participants perceived AR images to be brighter than the reference when using glasses with higher transmittance. These results suggest the presence of an additional contrast effect on brightness perception in AR glasses with half mirrors.

JIST-First Automotive Paint Defect Classification: Factory-specific Data Generation using CG Software for Deep-learning Models,

Kazuki Iwata¹, Haotong Guo¹, Ryuichi Yoshida², Yoshihito Souma², Chawan Koopipat³, Masato Takahashi¹, and Norimichi Tsumura^{1,4};

¹Chiba University (Japan), ²Konica Minolta, Inc. (Japan), ³Chulalongkorn University (Thailand), and ⁴Hiroshima University, Hiroshima University Hospital (Japan)

see JIST 67(5)/

DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050412

In recent years, the advances in technology for detecting paint defects on exterior surfaces of automobiles have led to the emergence of research on automatic classification of defect types using deep learning. To develop a deep-learning model capable of identifying defect types, a large dataset consisting of sequential images of paint defects captured during inspection is required. However, generating such a dataset for each factory using actual measurements is expensive. Therefore, we propose a method for generating datasets to train deep-learning models in each factory by simulating images using computer graphics.

12:45 – 14:00 LUNCH BREAK

PRINTING AND NAMING

Session Chair: Kristyn Falkenstern, Digimarc (US)

14:00 – 15:00

- 14:00 **JIST-first The Exploration of Specific Associations from Words to Colours**, Yun Chen¹, Jie Yang², Fan Zhang¹, Kaida Xiao³, and Stephen Westland³; ¹Beijing Institute of Technology (China), ²Beijing Institute of Graphic Communication (China), and ³University of Leeds (UK) see JIST 67(5)/DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050401

This study mainly focused on exploring the associations between words and colours. Colour association expresses a specific relationship between colour and various concepts or objects. However, it is noticed that when colour association is discussed, it is often in one direction; from colours to concepts. In this study, it is posited that colour association is bidirectional, meaning that we can also start with a word or concept and answer the question which colour or colours are associated with it. A psychophysical experiment was carried out to collect specific colour associations from target words. In the results, the strong similarity of the associated colours for each word was presented, meaning that people selected similar colours for each word. The study also indicated that different word classes have different degrees of association with colours. This study elucidates strong associations from words to colours, an important contribution of this work is to emphasise the direction word→colour in terms of colour association.

- 14:20 **Maximizing Neugebauer Primary Control: Beyond Halftoning**, Peter Morovic, Hector Gomez, Utpal Sarkar, and Sergio Eichebehere, HP Inc. (Spain); and Jan Morovic, HP Inc. (UK) . . 171

A pattern that is to be formed by a colorant on a substrate is defined in terms of the halftone image that instructs a printing system. This image contains information at each pixel as to which colorants to use at which drop states, i.e., Neugebauer Primaries (NPs) such as CC (two drops of cyan ink) or CM (a drop of cyan and a drop of magenta ink). However, the transformation from this digital input to a final printed pattern involves other steps as well as physical, colorant and substrate interaction effects. An important contributor to the final output is the partitioning of a halftone image into its complementary sub-images that are printed in each pass of a multi-pass or multi-bar printing system (common in inkjet). Typically, great attention is given to the goodness of a halftone image—good pattern distribution, good NP and ink choices—however, partitioning can also have a significant impact on the output both in terms of avoiding unwanted physical interactions (e.g., coalescence, alignment artifacts) and exercising control over the pattern. This can lead to closer correspondence to the halftone and improved print properties (such as grain and robustness) and can be achieved by co-optimizing halftoning (responsible for the spatial distribution of the halftone image) and partitioning (responsible for distributing it among the N passes or bars of a given printing system). The results are not only good overall halftone images as has been the case already, but also good partial halftone sub-images whose gradual printing in different passes results in maximized NP control and thereby its effect on the printed color.

- 14:40 **On the Cardinality of Color Stimulus Properties**, Peter Morovic, HP Inc. (Spain), and Jan Morovic, HP Inc. (UK) 178

When describing “how many colors” can be represented or reproduced by a given system or device, volume (or gamut volume) is often used. While it has a rightful place and is a valid way to describe a range of colors, it is an incomplete and indirect answer to the original “how many?” question. In this paper a first principles based approach is applied to this question, starting with delimiting the validity of any

possible answer by being explicit about assumptions about domain (dimensionality, encoding bit-depth, coordinate system or color space. etc.). Furthermore, no real-world data exists without a reference to a measurement device, which in turn has to consider sources of noise: physical surfaces whose color or spectral measurements differ by less than the level of noise of that device, cannot be considered as distinct. These assumptions directly affect possible answers to the initial question of how many colors or color stimulus properties there are. Starting from reflectances, their quantization and measurement noise as well as colorimetry are analysed in a variety of color spaces and the concepts of cardinality and colorimetric errors are used. The result is not a single answer but both an exploration of the effects of the assumptions and a characterization of their dependence. For example, results show how quantization and measurement error can have a significantly larger impact than may be intuited, likewise, the same analysis in CIE LAB, CIE CAM16 and CAM16-UCS yields substantially different answers (and may be applicable in different contexts), which also highlights current limitations of these spaces and color difference metrics. Additionally, a cardinality analysis can also be performed in a biological domain of retinal responses, which bridges the physical and psychophysical domains. As will be shown, precise answers can be given under specific and explicit assumptions, but in a general context, the answer always has to be “it depends”.

INTERACTIVE POSTERS AND EXHIBIT

15:00 – 16:45

Discuss the Interactive (poster) Papers with their authors and help select the CIC31 Cactus Award winner. Exhibits are also open during this time.

IMAGING NOTRE-DAME DE PARIS

Session Chair: Jérémie Gerhardt, DNEG (Canada)

16:45 – 17:30

Upraising Challenges of 3D Digitization Strategies in the Framework of the Notre-Dame de Paris Scientific Worksite (Invited Focal), Anthony Pamart, French National Centre for Scientific Research (France) *

In the framework of Notre-Dame de Paris scientific worksite, the Digital Data working group has forged an innovating digital ecosystem. Day after day, a digital twin of the cathedral is meticulously tailored to cater to the diverse needs of scientists from various disciplines. This presentation unveils saliency points of this unprecedented research framework, born from cutting-edge 2D/3D digitization strategies. A captivating journey is presented from a series of past and ongoing real-based modeling experiences on this emblematic heritage site.

CONFERENCE RECEPTION

17:30 – 20:00

Enjoy the city of lights with a panoramic view of the city and Seine atop the Zamosky Tower. Sponsored by Meta.



*No proceedings paper associated with talk.



FRIDAY 17 NOVEMBER 2023

CLOSING KEYNOTE AND AWARDS

Session Chair: Carol Payne, unaffiliated (US)

9:00 – 10:10

Colour Science vs. Colour Engineering in High-End Motion Picture,

Daniele Siragusano, FilmLight (Germany) *

Professional VFX and Finishing Applications rarely use cutting-edge colour science research results.

It seems that every software vendor reinvents the wheel of colour management over and over again. Even open-source initiatives like the Academy Colour Encoding System (ACES) utilize little of the findings produced by academia in recent years.

Almost every blockbuster movie is produced within a unique colour management environment created by a specialised “Inhouse Colour Scientist” in Post Facilities. Every camera manufacturer ships with its proprietary “Colour Science”. Every Colour Grading Software has custom colour models for every step in the process.

Why is this so?

It seems that the requirements for high-end motion picture workflows are very special and not well-established in the academic environment.

This keynote formalizes some of the most critical requirements for image algorithms in motion pictures, hoping to better align Colour Science and Colour Engineering for the big screen.

MULTI- AND HYPER-SPECTRAL

Session Chair: Maliha Ashraf, University of Cambridge (UK)

10:10 – 12:30

10:10 **JIST-first Efficient Hyperspectral Data Processing using File Fragmentation**, C. Caruncho, P. J. Pardo, and H. Cwierz, Universidad de Extremadura (Spain) see JIST 67(5)/ DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050403

In this article, we present a method for processing hyperspectral data in an easy and quick manner. We explain how we split the hyperspectral cube in different sections to be processed using fewer resources. We describe the processing, which includes extraction of the raw data along with white and black calibration data, calibration of the data and application of desired light source, color space, and gamma transformation. We then present a built-in software, including an easy interactive Graphical User Interface (GUI) that will allow fellow researchers to process hyperspectral images in a simple fashion.

10:30 **JIST-first Comparison of Pigment Classification Algorithms on Non-flat Surfaces using Hyperspectral Imaging**, Dipendra J. Mandal, Marius Pedersen, and Sony George, Norwegian University of Science and Technology (Norway); and Clotilde Boust, Center for Research and Restoration of Museums of France (C2RMF) (France) see JIST 67(5)/ DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050403

Cultural heritage objects, such as paintings, provide valuable insights into the history and culture of human societies. Preserving these objects is of utmost importance, and developing new technologies for their analysis and conservation is crucial. Hyperspectral imaging is a technology with a wide range of applications in cultural heritage, including documentation, material identification, visualization and pigment classification. Pigment

classification is crucial for conservators and curators in preserving works of art and acquiring valuable insights into the historical and cultural contexts associated with their origin. Various supervised algorithms, including machine learning, are used to classify pigments based on their spectral signatures. Since many artists employ impasto techniques in their artworks that produce a relief on the surface, i.e., transforming it from a flat object to a 2.5D or 3D, this further makes the classification task difficult. To our knowledge, no previous research has been conducted on pigment classification using hyperspectral imaging concerning an elevated surface. Therefore, this study compares different spectral classification techniques that employ deterministic and stochastic methods, their hybrid combinations, and machine learning models for an elevated mockup to determine whether such topographical variation affects classification accuracy. In cultural heritage, the lack of adequate data is also a significant challenge for using machine learning, particularly in domains where data collection is expensive, time-consuming, or impractical. Data augmentation can help mitigate this challenge by generating new samples similar to the original. We also analyzed the impact of data augmentation techniques on the effectiveness of machine learning models for cultural heritage applications.

10:50 – 11:30 COFFEE BREAK AND DEMONSTRATION SESSION

11:30 **Standard Representation Space for Spectral Imaging**, Jean-Baptiste Thomas, Université de Bourgogne (France); Pierre-Jean Lapray, Université de Haute-Alsace (France); Max Derhak, ONYX Graphics Inc. (US); and Ivar Farup, Norwegian University of Science and Technology (Norway) 187

The variety of spectral imaging systems makes the portability of imaging solutions and the generalization of research difficult. We advocate for the creation of a standard representation space for spectral imaging. We propose a space that allows connection to colorimetric standards and to spectral reflectance factors, while keeping a low and practical dimension. The performance of one instance of this standard is evaluated through simulations. Results demonstrate that this space may show reduced performance in accuracy than some native camera spaces, especially instances with a number of bands larger than the standardized dimension, but this limitation comes with benefit in size and standardization.

11:50 **Noise Prism: A Novel Multispectral Visualization Technique**, Trevor D. Canham¹, Javier Vazquez-Corral², David L. Long³, Richard F. Murray¹, and Michael S. Brown¹; ¹York University (Canada), ²Universitat Autònoma de Barcelona / Computer Vision Center (Spain), and ³Rochester Institute of Technology (US) . . 193

A novel technique for visualizing multispectral images is proposed. Inspired by how prisms work, our method spreads spectral information over a chromatic noise pattern. This is accomplished by populating the pattern with pixels representing each measurement band at a count proportional to its measured intensity. The method is advantageous because it allows for lightweight encoding and visualization of spectral information while maintaining the color appearance of the stimulus. A four alternative forced choice (4AFC) experiment was conducted to validate the method's information-carrying capacity in displaying metameric stimuli of varying colors and spectral basis functions. The scores ranged from 100% to 20% (less than chance given the 4AFC task), with many conditions falling somewhere in between at statistically significant intervals. Using this data, color and texture difference metrics can be evaluated and optimized to predict the legibility of the visualization technique.

*No proceedings paper associated with talk.

12:10 **Multispectral Imaging based on a Multichannel LED System and RGB Camera**, Hui Fan and Ming Ronnier Luo, Zhejiang University (China) **199**

In this study, a multispectral imaging system with an RGB camera and a multichannel LED system was investigated. Firstly, it was proposed to generalize a previous method to optimize the flexible combinations of no more than three LED channels in each light source. The systems of 6-channel, 9-channel, and 12-channel were obtained, and their performances were compared with a typical 3-channel system under D65. Subsequently, the systems using single LED channels as light sources were explored. Two different methods (single-light and single-channel) were developed by selecting different numbers of the optimal lights or system channels. It was found the single-channel system outperformed the system using combined LED channels in terms of the spectral reconstruction accuracy. However, it should be noted the single-channel system required significantly more captures than the method by combining three channels in a light.

12:30 - 13:45 LUNCH BREAK

MATCHING AND DISPLAYS

Session Chair: Romain Bachy, Meta Reality Labs (US)

13:45 - 15:05

13:45 **JIST-first Matrix R-based Visual Response to Optimal Colors and Application to Image Color Gamut Expansion**, Hiroaki Kotera, Kotera Imaging Laboratory (Japan) see JIST 67(5)/DOI: 10.2352/J.ImagingSci.Technol.2023.67.5.050414

The optimal colors with maximum chroma at constant lightness present an ideal target for the colorants pursuing the ultimate wide color gamut. MacAdam proved that optimal colors are composed of square pulse-shaped spectra with at least two transition wavelengths λ_1 and λ_2 whose reflectances change from 0 to 1 or 1 to 0. The optimal color gamut is created from two-types, a convex-type with reflectance 1.0 in $w = \lambda_1 \sim \lambda_2$ and 0.0 otherwise, or a concave-type with reflectance 0.0 in $w = \lambda_1 \sim \lambda_2$ and 1.0 otherwise. It takes a high computation cost to search the optimal color candidates in high precision and to create the 3D color gamut. In addition, the human visual spectral responses to the optimal color spectra remain unknown. This paper (1) proposes an alternative simple method for creating the optimal color gamut with GBD (Gamut Boundary Descriptor) technique, (2) clarifies how human vision spectrally respond to the optimal colors based on Matrix-R theory, for the first time which was unknown until now, and (3) presents centroid-invariant novel color gamut expansion method considering the optimal color as an ideal target and finally apply it to actual low-saturation images to verify its effect.

14:05 **Effect of Display Characteristics and Color Reproduction Method in Computerized Color Vision Test**, Dan Zhang, Shining Ma, Yue Liu, Yongtian Wang, and Weitao Song, Beijing Institute of Technology (China) **205**

A simulation was performed using simulated displays to examine how the results of the computerized color vision test are influenced by display characteristics, and color reproduction methods. In this work, the color difference between the background and the number in the test plates was employed to quantify the visibility of the target number in the computerized test. The results have indicated that for the color-appearance-based reproduction method, the impact of display characteristics on the target visibility is minimal except for the displays with extremely narrow bandwidth. While for the tristimulus-based reproduction method, it is necessary to consider display characteristics for the computerized color vision test.

14:25 **Analyzing Perceptual Uniformity using Jacobian Determinants**, David A. LeHoty, Independent Researcher (US), and Charles Poynton, Independent Researcher (Canada) **211**

The CIE LAB color space was established by color scientists to be approximately perceptually uniform. The $Y'C_B C_R$ color space is widely assumed by video engineers to be approximately perceptually uniform. However, these two color spaces have quite different transforms from tristimuli (radiometric) coordinates; they clearly cannot have the same perceptual performance.

It is instructive to ask: Where in color space is $Y'C_B C_R$ quantization the worst, when evaluated in terms of LAB? And, conversely, where in color space does LAB quantize most coarsely, when evaluated in Euclidean $Y'C_B C_R$ difference?

The Jacobian corresponding to a color coordinate in 3-space is a 3×3 matrix of partial derivatives. The determinant of that matrix is analogous to volume. We compute numerical Jacobian determinants to explore how unit LAB volumes at sample points spanning a target color space map to volumes in $Y'C_B C_R$. Where that volume is quite large, we expect poor perceptual performance of $Y'C_B C_R$. Where that volume is quite small, $Y'C_B C_R$ is over-quantizing, and may have poor codeword utilization—but in such regions it's reasonable to suspect the performance of LAB.

We present “heat maps” that visualize where $Y'C_B C_R$ performs poorly compared to LAB (and vice versa).

14:45 **The Influence of Interreflections on Shape from Fluorescence**, Irina-Mihaela Ciortan, Sony George, and Jon Yngve Hardeberg, Norwegian University of Science and Technology (Norway) . **215**

Fluorescence is an optical phenomenon, specific to certain materials that absorb light with higher energy and re-emit it at lower energy, with unnoticeable time latency. Due to this so-called Stokes shift, fluorescent materials pose several challenges in image capture, where usually a filtering set-up is required at the illumination and/or sensing ends. Nevertheless, fluorescence emission is diffuse, which was previously used in shape from photometry models. In this work, we target the shape from fluorescence method for a specific category of materials: those with overlapping reflectance and fluorescence signals. In particular, we investigate how the self-interreflections (light bounces off a surface that get re-reflected by the surface itself) change the appearance of scenes with such fluorescent materials and how this affects the shape estimation with a photometric stereo model. To avoid instrumental artifacts inherent in real image capture setups, we perform our analysis on a synthetic dataset of multi-light images, generated with a physically-based spectral renderer that supports fluorescence.

15:05 - 15:30 COFFEE BREAK

APPLICATIONS

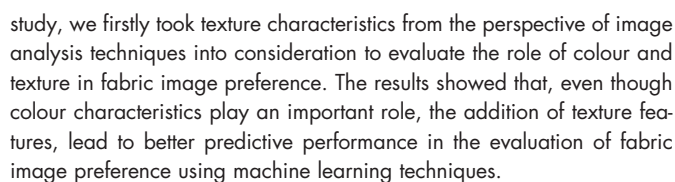
Session Chair: Luke Hellwig, Samsung (US)

15:30 - 16:30

15:30 **The Role of Colour and Texture on Fabric Image Preference**, Qinyuan Li, Kaida Xiao, Michael Pointer, and Ningtao Mao, University of Leeds (UK) **221**

Colour and texture characteristics convey most of the information of an image and influence human perception as contributing factors to perceived preference. How the colour, together with the texture characteristics affects fabric image preference is not fully understood. In the present





An efficient computational characterization of real-world materials is one of the challenges in image understanding. An automatic assessment of materials, with similar performance as human observer, usually relies on complicated image filtering derived from models of human perception. However, these models become too complicated when a real material is observed in the form of dynamic stimuli. This study tackles the challenge from the other side. First, we collected human ratings of the most common visual attributes for videos of wood samples and analyzed their relationship to selected image statistics. In our experiments on a set of sixty wood samples, we have found that such image statistics can perform surprisingly well in the discrimination of individual samples with reasonable correlation to human ratings. We have also shown that these statistics can be also effective in the discrimination of images of the same material taken under different illumination and viewing conditions.

Color performance is an important safety and performance attribute of endoscopes. An endoscope that exhibits poor color performance inadequately reproduces color images and may make it difficult for the endoscopist to visualize features needed for diagnostic or therapeutic tasks. Various color performance testing methods have been developed to evaluate color fidelity of endoscopes since 1987. However, these testing methods have limited utility because most endoscopes cannot and do not intend to reproduce the original color faithfully. In this work, endoscope color performance is reviewed by evaluating preservation of color contrast between patches and preservation of the patch order in lightness, hue, and chroma. The analysis method was implemented as the Color Performance Review (CPR) tool and is available in the catalog of Regulatory Science Tools published by FDA/CDRH/OSEL.

Jérémie Gerhardt, DNEG (Canada); Javier Vázquez Corral, Universitat Autònoma de Barcelona (Spain); and Carol Payne, unaffiliated (US)

16:30 – 16:35

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

CIC31 APPENDIX A

EXTENDED **ABSTRACTS**



Overview of Spectral Sensitivity Estimation Without a Camera

Grigory Solomatov, Derya Akkaynak; Haifa University, Haifa, Israel

Extended Abstract

Consumer digital cameras are not tools designed for scientific imaging, i.e., they are not scientific light-measuring devices [3, 6, 10]. Yet their outputs—digital photos and videos—constitute major sources of data for image processing, colorimetry, computational photography, computer vision, and machine learning. Typically, research utilizing consumer camera imagery focuses on the development of filters or algorithms that alter the visual appearance of images, or on the understanding of scene content and structure with downstream goals like recognizing, tracking, or counting objects. For many of these goals, successfully recovering scene reflectance and/or illumination is key (and often the main goal itself), but these tasks are complicated by the fact that consumer cameras do not capture colors in a standardized way [14].

Each camera captures colors in its own, device-specific color space. This is because manufacturers make different design choices for each sensor, which materialize within the limitations inherent to silicon-based semiconductor technology [5]. As a result, each make and model of camera is characterized by its unique set of spectral sensitivities that define how that camera responds to light. Effectively, this means that different cameras will register a different set of RGB values for a given scene—even if the scene is imaged under identical conditions [9]. If the camera’s color bias could be eliminated, the recovery of scene reflectance (e.g., for material property estimation [13], spectral super-resolution [8], etc.) and/or scene illumination (e.g., for computational color constancy [11], image relighting [7], data augmentation [2] etc.) could be achieved simpler and faster, and with more consistent results across cameras.

Unfortunately, however, manufacturers of consumer cameras rarely make spectral sensitivity curves available, and the burden falls on the researchers to derive them. Their derivation requires the stimulation of the camera’s sensor with monochromatic light across the entire wavelength range to which it is sensitive. Such light can be obtained through the use of a monochromator or a spectrally-tuneable light source, but these optical instruments are generally too specialized and expensive to be found in most research labs. A seemingly lower cost and complexity alternative is to use photos of calibrated color targets, but with this indirect option comes a hidden cost: the implicit requirement that the illumination under which the color target is imaged is also known. In practice, this either means that the light source is calibrated, or its spectrum is measured with a spectrophotometer; necessitating, again, that the user has access to non-standard hardware.

Even when the light spectrum is known, photos of color charts do not guarantee a “good enough” estimate

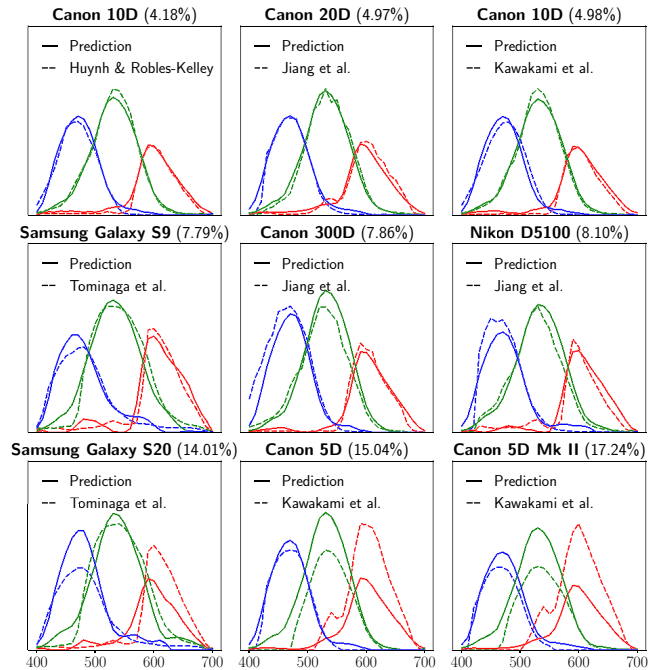


Figure 1. Nine spectral sensitivity reconstruction results from leave-one-out validation of our method on 51 ground-truths available in the literature. Top row: best results, middle row: median results, bottom row: worst results. The percentage specifies relative full-scale error. It should be noted that the typical disagreement between conflicting “ground-truths” in the literature is about 7%, and can be as high as 17%, which contributes to the observed error of our method.

of curves because there are too many unknowns in camera spectral sensitivities and not enough color chart patches whose reflectances are linearly independent [4]. The ill-posed nature of the problem introduces new challenges due to the need to constrain the solutions to a “realistic” space. Furthermore, the commonly used image formation model does not take into account the optoelectronics of the camera [12], making it difficult to relate the captured RGB values to the predicted ones. Finally, even if not limited by hardware or cost, it is not uncommon that researchers work with imagery captured by cameras that they actually do not have in their possession. Consequently, the missing knowledge regarding the spectral responses of consumer cameras hampers the otherwise fruitful utilization of a consumer electronic device in academic research.

Our own research in computer vision has been held back because we did not have the spectral sensitivities of the ever-evolving set of consumer cameras that produce the

imagery we work with, and this motivated us to search for a solution that did not require: 1) any specialized hardware, 2) a color chart photo taken by the camera, or 3) physical access to the camera itself. Unlike how it may seem at first glance, this is not an impossible task—one simply has to be aware of the wealth of publicly available data regarding colorimetric mapping of consumer digital cameras. Here, we describe a method that satisfies these requirements with reconstruction errors that are, on average, as low as those that can arise due to manufacturing imperfections between two copies of the same camera.

Our key observation is the following: Among the tags specific to Adobe’s Digital Negative (DNG) format [1], are color transformation matrices prefixed ColorMatrix. These 3x3 matrices map camera-specific colors to the standard CIE XYZ color space under a known illuminant. Calibrated by the manufacturer, Adobe, or third-party companies and appended to image metadata by the Adobe DNG Converter, each DNG file includes at least one ColorMatrix tag, whereas frequently, two matrices per camera can be found¹. In the common case when two matrices are available per camera, they are generally calibrated under illuminant A (tungsten, CCT≈2856K) and D65 (daylight, CCT≈6504K). We use these matrices to construct a linear system of equations which contains the sought spectral sensitivities in its solution space; and this solution space can be further constrained using an autoencoder trained on database of ground-truth spectral sensitivities from the literature. Using this novel approach we make the following contributions:

1. a zero-cost method with which to obtain reasonable estimates of camera spectral sensitivities, and
2. predicted spectral sensitivities of more than 1,000 makes and models of cameras that are currently in the market.

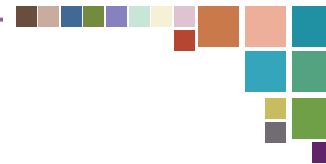
A selection of our reconstruction results is shown in Figure 1. This work has been presented at IEEE ICCP 2023 [15].

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¹Since the release of DNG version 1.6.0.0, a third color matrix is also specified for some cameras [1].





Forward and inverse colour calibration models for OLED displays

Maliha Ashraf¹, Dounia Hammou¹, Rafał K. Mantiuk¹

¹Department of Computer Science and Technology, University of Cambridge, UK

Abstract

We compare different methods of colour calibrating OLED 4-primary displays. The forward models use different colour transformation techniques to predict device-independent tristimulus values from device native RGB values. The inverse models transform the device-dependent tristimulus values to predict the native RGB values that could produce the required colour. We found that the performance of the models depended on the display characteristics and the models that performed better in terms of forward model error were not necessarily better for inverse model performance as well.

Background

OLED (Organic Light Emitting Diodes) displays are becoming increasingly popular because of their ability to achieve high luminances along with larger colour gamuts. To boost the luminance range and reduce power consumption, many OLED display manufacturers use an additional white primary to supplement the red, green, and blue channel responses. However, this makes OLED displays challenging to calibrate as the drive signals as the relation between input and emitted light becomes more complex. Moreover, OLED display manufacturers also face additional engineering constraints, such as limiting power consumption, limit on current density, pixel burn-in, which add additional complexity to the display's control and consequently its characterisation.

The existing OLED colour models in the current literature were evaluated in terms of the accuracy of the forward display model, which maps input display-encoded pixel values (e.g. sRGB or BT.2100) into colorimetric values of emitted light (XYZ or linear BT.2020 RGB) [1, 2, 3]. However, for most practical applications, we are interested in the inverse display model, which maps colorimetric values (which we want to display) into display-encoded pixel values. For that reason, in this paper, we evaluate all models in terms of the accuracy of the inverse display model, in addition to the forward display model, and also test the error introduced by computing the inverse of the model. It should be noted that display models for OLED are not directly invertible (bijective functions) because of the look-up tables, interpolation, and decision boundaries. For that reason, the performance of the inverse display model can be worse than that of the forward display model.

Display Measurements

To collect data for our model comparison, we measured the colour response of two OLED TVs: two 55-inch OLED TVs: LG OLED Evo G1 (firmware version: 03.34.80) and G2 (firmware

version: 03.21.30). The Psychtoolbox software [4] running with MATLAB in a Windows 10 environment (Windows HDR enabled) was used for presenting the measurement patches with HDR10 and 16-bit floating point precision per colour channel enabled. We collected the measurements using the same settings that were used for both displays to assure fairness in the comparison. The measurements were done in a dark room. For the colour settings, the native gamut was chosen. To avoid any unwanted alteration of the display outputs, all auto adjustment and enhancement settings were turned off. Additionally, both GSR (Global Sticky Reduction) and TPC (Temporal Peak Luminance Control) were disabled using the displays' service menus. These settings prevent image retention and pixel burn-in by dimming the brightness of the image. However, this is not desirable if we want to colour calibrate the displays accurately.

We collected 3 sets of measurements (XYZ) from each of the two OLED displays that we will call: i) ramps, ii) grid, and iii) test using the Konica Minolta CS-200 colorimeter. The measurements were done by displaying the colour in a rectangle in the middle of the screen. The test patches covered 5% of the total screen area and the rest of the screen was black.

Ramps The individual responses of each of the r, g, b, and w channels were measured using 120x4 HDR10 pixel values. These measurements are used to estimate the EOTF of the displays.

Grid A full 13x13x13 grid of RGB pixel values was measured for HDR10 pixel values. The grid measurements are used to optimise the transformation matrices and to compute 3D LUTs.

Test The performances of the models were tested using these measurements. We used the XYZ measurements of the colours of the X-Rite ColorChecker taken under Illuminant C from [5] and scaled them to five different luminance levels: 1, 4.7, 22, 106 and 500 cd/m² to generate a set of 120 colour coordinates and measured the display responses.

Models

Three sub-gamuts This model is based on the three-matrix method proposed in [3]. Bodner et al. divided the four-primary rgbw gamut into three-subgamuts rgw, rbw and gbw which assumes that three out of four primaries drive the display for any given colour depending on its location in the sub-gamuts, and then finds the correction matrices for reducing XYZ measurement errors between a reference spectroradiometer and test colorimeter. We use the same approach to estimate the transformation

matrices between linear RGB pixel values and the corresponding RGB BT.2020 values. The transformation matrices were estimated using the grid measurements. The native RGB values were assigned to their respective sub-gamuts by finding the minimum of the three RGB linear values and the M_{RGW} , M_{RBW} , and M_{GBW} matrices were optimised by MATLAB GlobalSearch with CIE ΔE_{00} as the error function. We extended the model by adding an extra compensation step, in which a 3D LUT was used to correct residual errors.

PLCC-based compensation (PC) The PLCC-based compensation model is proposed in Tian et al. [2] in which the PLCC (Piece-wise Linear interpolation assuming Constant Chromaticity) [6] method is used to predict the intermediate XYZ values and then a 3D LUT is mapped to compensate for the remaining prediction errors.

Colour mixing In the model proposed by Sun and Luo [1], two transformation matrices are used — one for high and one for low chroma colours. The high chroma matrix (M_{rgb}) is estimated using the XYZ values of the rgb primaries. The low chroma matrix (M_{gray}) is estimated by scaling (M_{rgb}) to match the response of the w primary. The final XYZ values are the weighted sum of the XYZ values from the high and low chroma matrices.

Polynomial regression We tested the 3rd order polynomial regression model proposed in Sun and Luo [1]. The XYZ values are predicted by a 14x3 matrix with the polynomial terms: ($R, G, B, R^2, G^2, B^2, R^3, G^3, B^3, RG, GB, BR, RGB, 1$). The coefficients of the polynomial matrix are optimised using MATLAB GlobalSearch with CIE ΔE_{00} as the error function to be minimised. Our 13x13x13 grid measurements are used for this optimisation.

RGBW gamut We tested a model which works on a simple assumption of independent RGBW primaries where linear combinations of each of the four pixel responses produce the combined colour response. The final display colour output is a non-linear function of the four sub-pixel responses. We tested the model to see whether this simple assumption could compete with the more sophisticated models outlined above. The coefficients of the XYZ to RGBW linear transformation matrix are optimised with CIE ΔE_{00} as the minimising function.

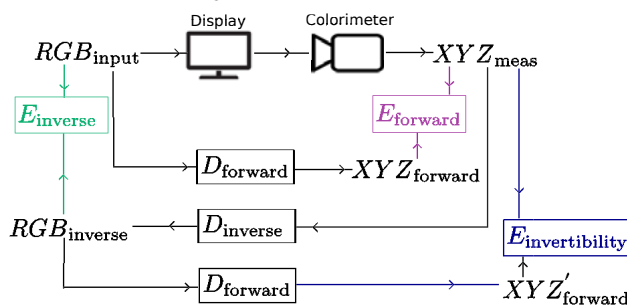


Figure 1. Model validation flowchart. $D_{forward}$ represents the forward models and $D_{inverse}$ represents the inverse models. $E_{forward}$ is the forward model error, $E_{inverse}$ the reverse model error, and $E_{invertibility}$ is the invertibility test error

Validation

We use 3 metrics to test the performance of the different models. All the testing was done using the 120 *test* measurements data set. The inputs of the three error metrics are shown in Figure 1.

Forward model The forward model error ($E_{forward}$) is the CIE ΔE_{00} colour difference between the output of the display forward model and the measured XYZ colour values. The XYZ values are converted to $L^*a^*b^*$ values with the highest value of the w primary as the white point.

Inverse model The inverse model error ($E_{inverse}$) is the difference between the PQ-encoded RGB values in the native colourspace of the display. The measured XYZ values are transformed to the native RGB pixel values via the respective inverse models.

Invertibility test For this test, we pass the XYZ measurements through the inverse model to predict the native RGB values and then pass those values through the forward model to predict the XYZ values again. This test tells us the extent of the invertibility of the model. A perfectly invertible model should give the error of 0. However, due to the use of interpolation, look-up tables, and decision boundaries, such error is non-zero for more complex models.

Results

Figure 2 shows the results of our three error metrics for the G1 and G2 displays. In terms of forward model performance, the 3-gamut model and the PLCC-based compensation model (PC) produce the smallest CIE ΔE_{00} for both G1 and G2 displays. The forward model errors for both the models are comparable for the G1 display, but PC shows a slightly lower error distribution than the 3-gamut model for the G2 display. We believe that the source of performance differences between the two displays is the difference in their internal EOTF curves.

The Colour Mixing (CM) model showed the smallest mean and median inverse model errors for the G1 display. For G2 display, the 3-gamut model along with the CM model showed the best performances. All the models show quite large maximum errors as compared to the forward model errors.

The results from the invertibility test show that the performances of the models are almost reversed for the two displays. The models that performed better for G1 are the worst performing ones for G2. Note that in this model, we apply both the inverse and forward models successively and this is not a measure of accurate colour transformation but of the invertibility of the models. The Polynomial and RGBW-gamut method use linear transformation matrices and show high invertibility for G1, but the opposite for G2. This could be because G2 (the more recent model) uses its white primary in a more non-linear way compared to G1.

Conclusions

We compared the performances of different state-of-the-art OLED colour calibration models for both forward and reverse transformations. We recommend the use of 3-gamut or PLCC-based compensation model method for the forward display char-



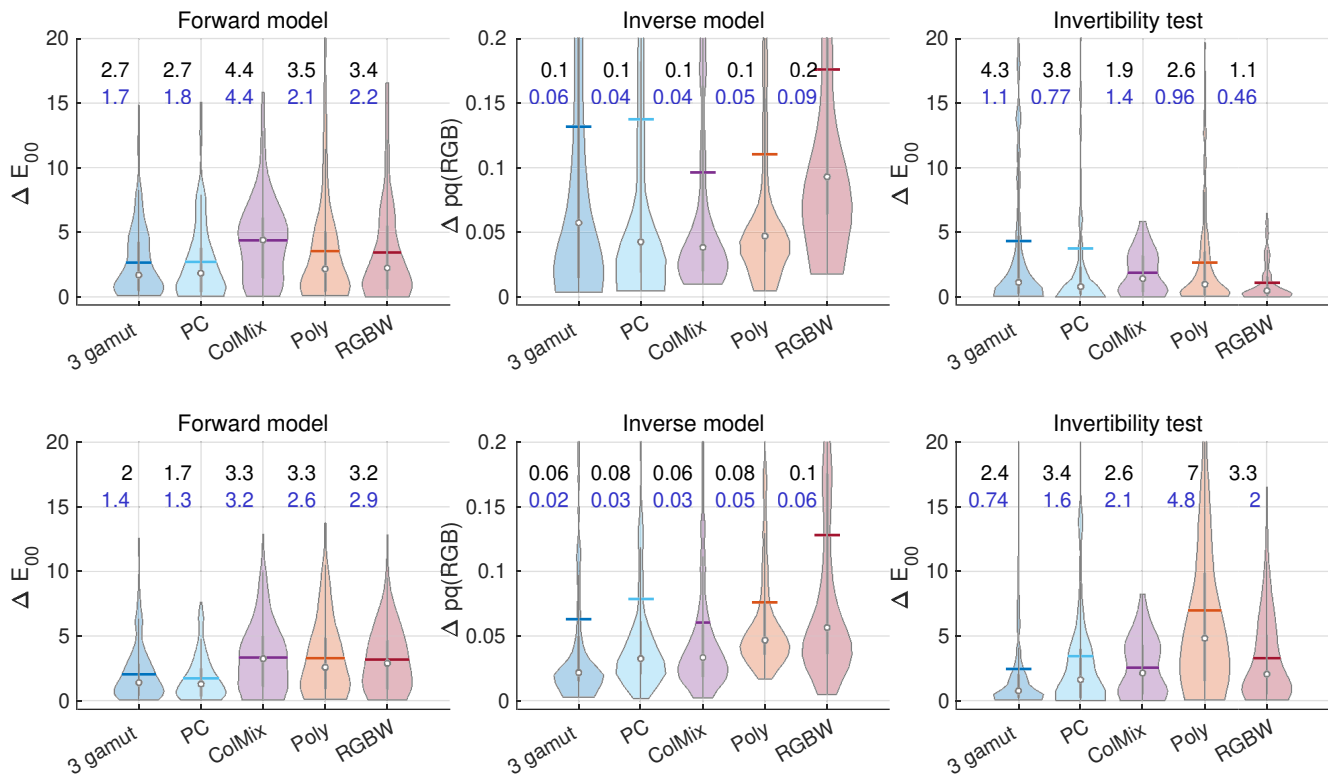


Figure 2. The distribution of errors for the G1 (top) and G2 display (bottom). The models are: 3-gamut, PLCC-based compensation (PC), Colour mixing (ColMix), Polynomial regression (Poly) and RGBW gamut. The white circle in each violin plots are the medians and the horizontal dash are the means. The black text at the top left of each violin is the mean, the blue text are the medians.

acterisation and either 3-gamut or Colour Mixing model depending on the luminance response characteristics of the display for inverse display characterisation. The comparisons demonstrate the need for further work in developing better colour characterisation models for OLED displays.

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