Image Quality and Change of Illuminant: An Information-Theoretic Evaluation

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Abstract
We investigate the influence of scene illuminant on perceived image quality. Given two multispectral images, an original and a reproduction (e.g., compressed, gamut mapped,...), we seek redundancies of perceived difference through changes of illuminant, and with regard to 5 so-called image difference features (IDF). In order to do this, we employ an information-theoretic perspective to measure variations of entropies in each IDF, w.r.t. various scene illuminants, and in the case of two particular kinds of distortions: spectral gamut mapping and a spectral reconstruction from a six-channel camera model. Our results indicate that changing the scene illuminant has a lesser influence on achromatic image difference features.

Introduction
Most recent studies on Image Quality Assessment (IQA) rely on greyscale or chromatic information to rate the difference between two images. The intent is to correlate as much as possible with human's judgment under specific viewing conditions. Yet, with the advent of spectral technologies, image appearance models and multichannel printing, there is a growing need for a higher dimensional IQA. Spectral acquisition, processing and reproduction methods (e.g. spectral gamut mapping, spectral separation, compression, dimensionality reduction), require a new range of measures for Spectral Image Quality Assessment (SIQA).

Although criteria such as classification or target detection accuracy are widely used for spectral quality in remote sensing applications, very little work has actually been done to evaluate spectral quality in terms of perception. In various spectral-based distances and divergence measures were studied for hyper- and multispectral image quality, with attempts to relate these quantities to perceptual meanings. Although they might correlate with human judgment in some cases, measures that operate directly in spectral space such as the popular Root-Mean Square Error or the Goodness-of-Fit Coefficient, are usually unable to properly do so. A reasonable explanation to this is that the very notion of color (at least in terms of perception) exists only when Viewing Conditions (VC) are specified. Without considering at least a scene illuminant and an observer model, no assumptions can be made on how reflectance spectra are interpreted by the human visual system. An alternative strategy is to pool the scores from a traditional image difference measures like CIE2000 over a variety of VC, but to which extent? How much, and which aspects of the perceptual difference between two images remain unchanged from one set of VC to another (e.g. from daylight to incandescent light)?

In this study, we investigate such questions, in order to better understand the key challenges in SIQA. We propose to use a set of 5 image-difference features introduced by Lissner et al. and to observe their behavior when the scene illuminant changes. In order to do this, we employ an information-theoretic perspective to measure variations of entropies in each feature, w.r.t. various scene illuminants, and in the case of two particular kinds of distortions: spectral gamut mapping and spectral reconstruction from a six-channel camera model. Note that the most influential VC feature is certainly the spectral power distribution of the scene illuminant. Therefore, this study focuses solely on changes of illuminant, while the remaining VC (e.g. standard observer) are assumed to be constant.

Image difference features
In order to better understand how image differences are changed with the scene illuminant, we rely on the Image-Difference Features (IDF) used for the Color Image-Difference (CID) measure. In the CID framework, the two images to compare are first normalized with an image-appearance model, including a CAT02 chromatic adaptation (as used by CIECAM02). This is to take into account “the human visual system’s capability to adjust to widely varying colors of illumination in order to approximately preserve the appearance of object colors” [16]. The images are then converted into the nearly perceptually uniform LAB2000HL color space. IDF maps are then computed by means of terms adapted from the SSIM index within sliding windows (see formulas in Appendix). Five maps are therefore obtained: Lightness-Difference map, Lightness-Contrast map, Lightness-Structure map, Chroma-Difference map and Hue-Difference map. Figure illustrates the workflow from spectral space to feature extraction. We refer to the original paper and the source code provided by Lissner et al. for further explanations about the measure.

Note that the CID measure compares tri-chromatic images, therefore each IDF map is intrinsically linked to certain viewing conditions. The conversion from reflectance data to CIEXYZ tristimuli, was made w.r.t. a CIE 2° standard observer, and a variety of illuminants. In a previous, recent work, we observed that CID scores computed for a few illuminants are able to predict image difference under a large variety. In this study, we aim to
Figure 1. Part of the CID workflow, from spectral space to feature extraction. The figure is partially extracted from [15].

quantify and better understand the variability of each IDF.

Redundancies

Given the IDF maps under a variety of illuminants, we wish to evaluate their respective content in terms of information. Measures based on Shannon’s entropy [19] provide an efficient probabilistic framework to do so. Moreover, when applied to data with perceptual attributes, they ensure that the abstract notion of information relates to a perceptual quantity. The entropy of an IDF map is a measure of its uncertainty. It is usually measured in bits, that is the number of bits required to code the full map. The more bits are required to code all the coefficients of the map, the more information it contains. We denote \( H(X) \) the entropy of the discrete random variable \( X \), which is estimated as follows:

\[
H(X) = - \sum_{x=0}^{N} p_x \log_2(p_x)
\]

where \( \{0 \ldots N\} \) is the range of the sample data (in the case our 8-bit IDF maps, \( N = 255 \)) and \( p_x \) is the probability density function of \( X \) (the probability that \( X \) takes the value \( x \)), usually estimated by the data’s histogram. Note that the use of base 2 for the logarithm is the reason why the unit of \( H(X) \) is the bit.

Figures 2a and 2b illustrate the interaction of a pair of spectral images and their respective renderings, in terms of information. The sought-after quantity in this study is the red zone in Figure 2a), a complex overlap of information between several variables, depicting the difference between the two images that is common to all illuminants. Not only do we aim to quantify it, we also wish to understand what it is made of, to evaluate which IDF’s are the least and most sensitive to illuminant changes. Measures based on the conditional entropy, defined as follows:

\[
H(X|Y) = - \sum_{x=0}^{N} \sum_{y=0}^{N} p_{x,y} \log_2 \left( \frac{p_{x,y}}{p_y} \right)
\]

where \( p_{x,y} \) is the joint density function of \( X \) and \( Y \), computed by their joint histogram.

On this basis, \( H(\mathbf{L}_{DL}^{D65}|\mathbf{L}_{DL}^{PC1}) \) denotes the gain of Lightness-Difference information for a D65 rendering and \( H_{L_{DL}}^{PC1} \) refers to the average over all illuminants in \( \Theta \). Note that we also allow the reference to be multi-dimensional, that is to measure the gain given not one but several PCs, such as \( H(\mathbf{L}_{DL}^{D65}, \mathbf{L}_{DL}^{PC1}, \mathbf{L}_{DL}^{PC2}) \). The greater the dimensionality of the entropy, the greater the number of samples required for a reasonable accuracy. Therefore, we consider only the two first PCs of \( \Theta \) in this study.

If the average gain of IDF information is low, it means that only a few PCs are sufficient to accurately predict the perceptual image difference under any illuminant. Figure 4 shows an example.
Figure 2. Diagram representation of information interactions. Each ellipse represents the information spanned by an image. The two largest ellipses, noted O and R (solid and dashed line) represent an original spectral image and a given reproduction (respectively). Note that it is likely (but not necessary) that a reproduction contains less information than the original. In (a), the smaller ellipses describe the renderings \( r_{\Theta_1} \) and \( r_{\Theta_2} \), under illuminant \( \Theta_1 \). The grayed areas therefore represent the information that is discarded by the human visual system, e.g. the identification of parameric pairs [14]. The white area represent the overlap of information between both renderings (mutual information), whereas the yellow parts depict the information that exist in one rendering but not the other, i.e. the image difference. In (b), a second illuminant is considered: \( \Theta_2 \). The red areas depict the overlap of perceived image difference, that is for example the artifacts that are equally annoying under both illuminants.

Experiments and Results

Illuminants

For our experiments, we used a total of 74 illuminants in \( \Theta \): four CIE daylights (D50, D65, D80 and D100), the CIE A and Fluorescent Series as well as the full collection made available by the National Gallery of London [22], which includes LED, fluorescent and tungsten-based lights. For the sake of clarity, Figure 3 depicts only the three first PCs extracted from this set. All illuminants were normalized to the intensity range [0, 1], including the synthetic ones (given that principal component analysis may produce negative values).

Images

The 8 multispectral images of natural scenes from Foster’s 2002 database [23] were used in this study. They contain 31 channels covering the visible wavelengths range.

To create distorted images, we rendered reproductions for each reference image based on three kinds of distortions:
• **Spectral gamut mapping 1**: We considered the spectral gamut of a Canon iPF5000 printer utilizing CMYKRGB inks, and a naive approach that uses CIELAB and D65 illuminant to map the out-of-gamut pixels to their closest in-gamut pixels, w.r.t. $\Delta E_{ab}^*$. From the resulting CIELAB pixels, printable metamers were selected randomly, yielding a spectral in-gamut image, denoted by R1.

• **Spectral gamut mapping 2**: With the same gamut, we applied the method presented in [5]. We used D65 and A as principal and secondary illuminants, respectively. The resulting spectral reproduction is denoted by R2.

• **Spectral camera model**: We simulated how a customized 6-channel Sinar camera with known spectral sensitivity functions would acquire the scenes. Reflectance curves were then reconstructed by means of the pseudo-inverse method (see for instance [24]), using a reduced set of Macbeth ColorChecker spectra [25]. No noise nor point spread functions were considered in the model. The resulting spectral reproduction is denoted by R3.

Figure 5 gives an example of renderings under D65. The conversion from reflectance data to CIEXYZ tristimuli was made w.r.t. a CIE $2^\circ$ standard observer. As previously explained, we assume that changing the illuminant has a far greater influence on the rendering than a change of observer.

**Results**

Figures 6, 7 and 8 show the results obtained. Note that over the 8 images of the database, we observed relatively small standard deviations overall. This shows a limited influence of the scene on these results.

We note that the three reproductions yield different trends, obviously depending on their relative characteristics. The naive gamut mapping engenders the worst predictability in terms of contrast and structure, which is in accordance to the fact that it does not consider any spatial information. On the other hand, the second gamut mapping presents a very good stability in terms of lightness-bases features. Not only do different kinds of distortion affect different IDFs, they also affect how these IDFs vary under different illuminants. Even considering a same gamut, two spectral gamut mapping approaches can render images that react in drastically different ways to illuminant changes. It seems however that these graphs have a few common trends. For instance, the least predictable attributes are always the chroma and hue, and particularly the latter. These chromatic IDFs also engender the largest drops between $H_{PC1}$ and $H_{PC2}$ as well as the largest standard deviations across our experimental data, especially in the case of R3. Otherwise, the $C_L$ is overall the best predictable IDF.

In the end, when considering a large variety of illumi-
nants, although one representative can be enough to predict variations of achromatic differences, chroma and hue discrepancies are more critical and thus require more information to be predicted with a sufficient accuracy.

Conclusion

We investigated the influence of scene illuminant on perceived image quality, from the perspective of information theory. Given two multispectral images, an original and a reproduction (compressed, gamut mapped...), we observed interesting trends in terms of redundancies of perceived difference through changes of illuminant, with regard to 5 so-called image difference features. We showed that not only do different kinds of distortion affect different quality features, they also affect how these features vary under different illuminants. Particularly, our preliminary results indicate that changing the scene illuminant has a lesser influence on achromatic image difference features. Consequently, spectral reproduction methods such as spectral gamut mapping or spectral reconstruction need not to consider these as much as chroma and hue preservation across illuminants. This conclusion creates new perspectives for instance for the design of a low-dimensional Profile Connection Space allowing to compare spectral image with a limited number of features.

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Appendix: Image Difference Features

The following equations describe the 5 IDFs used in [3] and investigated in this study. As previously explained, these terms are derived from the SSIM index. They are computed within sliding windows \(x\) and \(y\) in the compared images \(X\) and \(Y\) (resp.). Each pixel \(x\) consists of a lightness and two chromatic values: \(x = (L_x, a_x, b_x)\). The chroma of the pixel is defined as \(C_x = \sqrt{a_x^2 + b_x^2}\). Note that the LAB2000HL colorspace [17] is used in this study for it has improved properties regarding perceptual uniformity and hue linearity compared to CIELAB.

1. Lightness, chroma, and hue comparisons:

\[
\begin{align*}
L_L(x, y) &= \frac{1}{c_1} \Delta L(x, y)^2 + 1, \\
C_L(x, y) &= \frac{1}{c_4} \Delta C(x, y)^2 + 1, \\
H_L(x, y) &= \frac{1}{c_5} \Delta H(x, y)^2 + 1,
\end{align*}
\]

where \(\Delta L(x, y), \Delta C(x, y)\) and \(\Delta H(x, y)\) denote the Gaussian-weighted mean of pixel-wise Lightness, Chroma and Euclidean Hue differences computed for each pixel pair \((x, y)\) in the window.

2. Lightness-contrast comparison, according to [1]:

\[
c_L(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2},
\]

where \(\sigma_x\) and \(\sigma_y\) are the standard deviations in the lightness component of the sliding windows.

3. Lightness-structure comparison, according to [1]:

\[
s_L(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3},
\]

where \(\sigma_{xy}\) corresponds to the cosine of the angle between \(x - \bar{x}\) and \(y - \bar{y}\) in the lightness component.

The following values were used for the IDF parameters: \(c_1 = c_4 = 0.002, c_2 = c_3 = 10, c_5 = 0.02\).

References


[22] “Spectral power distribution curves, the national gallery: http://research.ng-london.org.uk/scientific/spd/”