Perceptual color difference assessment using histogram distance on hue histogram descriptor

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PERCEPTUAL COLOR DIFFERENCE ASSESSMENT USING HISTOGRAM DISTANCE ON HUE HISTOGRAM DESCRIPTOR

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ABSTRACT

In this paper, we propose a new color difference assessment scheme, with emphasis on hue attribute. The proposed measure is a full-reference difference predictor, which extracts hue histogram descriptors from a pair of color images to be compared and quantifies their difference. In order to achieve good correlation with subjective judgement, we exploit a preprocessor approximating the contrast sensitivity function of visual system, followed by a histogram distance function for circular data which corresponds to the way humans perceive difference. Performance of the proposed scheme is validated on benchmark datasets exhibiting perceptual degradation caused by gamut mapping. Experimental results indicate the effectiveness of the proposed metric against chromatic distortions, making it useful as an optimization module for color gamut mapping applications.

***Index Terms*—** color image, perceptual image difference, hue histogram descriptor, circular histogram, histogram distance

1. INTRODUCTION

The past decade has witnessed significant advances in digital imaging technologies which aim to provide consumers with rich visual experience in a wide range of applications, such as telecommunication, entertainment, and gaming industries. With this trends, perceptual assessment of image similarity/dissimilarity has become essential in the development/optimization of visual data processing algorithms. Assessment of image difference can be achieved in two ways, via subjective judgement and objective metric. Among them, objective computational metrics, capable of approximating perceived image difference of an average observer, e.g. mean opinion score (MOS), have been widely used in practical real-time applications. Numerous objective metrics have been proposed to predict perceived image difference in visual data. Recent studies [1, 2] noted that some representative methods, such as structural similarity (SSIM) index [3] and its extensions [4, 5, 6], yield accurate results on publicly available large-scale databases, e.g. LIVE [7], and CSIQ [8]. However, many conventional metrics are designed to rely on geometric features on grayscale domain either because of relative insignificance of chromatic information in their intended applications or because of computational efficiency. Apparently, they are not very successful in dealing with color images exhibiting chromatic deviations, e.g. images produced from color gamut mapping or tone mapping, since they overlook contribution of chromatic information in perceived difference [9]. In order to properly estimate the difference between color contents, we need to extract key dissimilarity indicators, i.e. features that are predictive of visual difference. Apparently such feature should be both highly correlated with visual perception as well as easily accessible [10].

In this paper, we mainly rely on the hue attribute of color signal to achieve effective color difference assessment. We focus on hue information due to its perceptual significance in estimating chromatic difference of visual stimuli. In color theory, hue is an attribute closely related to the dominant wavelength of visual signal, represented by angle around the achromatic axis. Due to its periodic nature, computational tools used for data on the line cannot be directly applied in hue data [11]. Presented method applies a spatial filter approximating contrast sensitivity function (CSF) of human vision to normalize the viewing distance of two images, then characterizes them by extracting hue histogram descriptors. Subsequently, attained histograms are compared through a histogram distance measure for circular data. This ensures that periodic nature of hue data is properly taken into account while comparing statistical properties of corresponding image regions. The effectiveness of the proposed scheme is evaluated on color gamut mapping databases, which contains a large number of images processed by popular gamut mapping algorithms (GMAs). Although histogram based descriptors has been popular for image retrieval purpose, to the best of our knowledge, there has been little research conducted on exploiting them in image quality/difference assessment. We believe the presented scheme will be useful for tuning of existing GMAs by employing it as the objective function, since one of the critical requirements for them is to minimize hue deviation during mapping process [12].

The rest of this paper is organized as follows. Section 2 demonstrates background knowledge related to existing histogram distance measures. Section 3 provides the detail of the proposed color difference prediction scheme. Experimental results are summarized in Section 4 and conclusion is drawn in Section 5.

2. PRELIMINARIES

Histogram-based local descriptors have been widely used in various computer vision tasks, especially for image retrieval, and color analysis. For comparison of histogram descriptors, a measure of dissimilarity between histograms should be defined. In this section, we provide a formal definition of histograms, and demonstrate representative distance measures between histograms.

2.1. Histogram Definition

Assume that m is a measurement, or feature, which can be one of n values contained in the set $M = \{m_1, \cdots, m_n\}$. Consider a set of k elements whose measurement of the value of m are $A = \{a_1, \cdots, a_k\}$ where $a_t \in M$. The histogram of the set A along the measurement m, represented by $\mathbf{Q}(m, A)$, is an ordered list (or n-dimensional vector) consisting of the number of occurrences of the discrete values of m among the m_t. Here, we can replace $\mathbf{Q}(m, A)$

with $\mathbf{Q}(A)$ without loss of generality, since we are interested in comparing the histograms of the same measurement. If $q_i(A)$ (i.e. bins of the histogram), $1 \leq i \leq n$, denotes the number of elements of A that have values m_i, then $\mathbf{Q}(A) = [q_1(A), \cdots, q_n(A)]$ where

$$q_i(A) = \sum_{t=1}^{k} C_{i,t}^A, \qquad C_{i,t}^A = \begin{cases} 1 & \text{if } a_t = m_i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The difference between two quantized measurement levels, e.g. m_i and m_j, is called the ground distance between i-th and j-th bin.

There exist three types of histograms depending on the types of measurements [13, 14]: i) nominal : each value of the measurement represents an instance of a particular semantic concept and there is no ordering among them, e.g. the last name of the students; ii) ordinal : measurement values are ordered, e.g. the age of the student; iii) modulo : measurement values form a ring due to periodic nature, e.g. any angular measurements. It should be noted that for modulo data, the ground distance between two measurement values is a function of $min(|m_i - m_j|, n - |m_i - m_j|)$ due to their circular nature, while the one for ordinal data is simply a function of $|m_i - m_j|$.

2.2. Representative Histogram Distances

Several measures have been used to quantify difference between two histograms, $\mathbf{P} = [p_1, \ldots, p_n]$ and $\mathbf{Q} = [q_1, \ldots, q_n]$ (assume that they are normalized, i.e. $\sum_{i=1}^n p_i = \sum_{i=1}^n q_i$). Histogram distance measures can be classified into two categories [13, 14, 15]: i) bin-to-bin, ii) cross-bin distance. The bin-to-bin measures only compare corresponding bins; they compare p_i and q_i for all i, but not p_i and q_j for $i \neq j$. Followings are some representative bin-to-bin measures.

- **Minkowski Distance** : A histogram is treated as a n-dimensional vector, and thus the standard vector norms can be used as distances between two histograms as follows:

$$D_{L_r}(\mathbf{P}, \mathbf{Q}) = \left(\sum_i |p_i - q_i|^r \right)^{1/r} \tag{2}$$

  where r is minkowski norm. Two popular examples are the Manhattan distance ($r = 1$) and the Euclidean distance ($r = 2$), denoted as L_1-norm and L_2-norm.

- χ^2 **Distance** : It is derived from the χ^2 test statistics and defined by:

$$D_{Chi}(\mathbf{P}, \mathbf{Q}) = \frac{1}{2} \sum_i \frac{(p_i - q_i)^2}{(p_i + q_i)} \tag{3}$$

  χ^2 distance particularly takes into account that the difference between bins of large values is generally less significant than the difference between bins of small values in many natural histograms.

- **Jeffrey Divergence (JD) Distance** : The Kullback-Leibler (KL) divergence, defined as $D_{KL}(\mathbf{P}, \mathbf{Q}) = \sum_i p_i \log(p_i/q_i)$, measures how efficient on average it would be to express one histogram using the other as the code-book. One drawback of KL distance is its non-symmetric property, i.e. $D_{KL}(\mathbf{P}, \mathbf{Q}) \neq D_{KL}(\mathbf{Q}, \mathbf{P})$. The JD distance, a variant of KL distance which satisfies the symmetric property, is defined by:

$$D_{JD}(\mathbf{P}, \mathbf{Q}) = \sum_i \left[p_i \log\left(\frac{2p_i}{p_i + q_i} \right) + q_i \log\left(\frac{2q_i}{p_i + q_i} \right) \right] \tag{4}$$

Aforementioned bin-to-bin distances are fast to compute since they only compare corresponding bins, but they may overemphasize the difference when there is a small translation in the overall distribution; a small shift of histogram values may significantly affect histogram distance [16]. On the other hand, the cross-bin measures address this alignment issue by taking into account the difference between non-corresponding bins.

- **Quadratic-Form (QF) Distance** [17] : It is defined as:

$$D_{QF}(\mathbf{P}, \mathbf{Q}) = \sqrt{(\mathbf{P} - \mathbf{Q})^T \mathcal{A} (\mathbf{P} - \mathbf{Q})} \tag{5}$$

  where the $n \times n$ matrix $\mathcal{A} = [a_{i,j}]$ is called a similarity matrix. The matrix elements $a_{i,j}$ encode similarity information between the i-th and the j-th bin. $a_{i,j}$ can be expressed in a way that $0 \leq a_{i,j} \leq 1$, with large $a_{i,j}$ denotes similarity (thus, $a_{i,i} = 1$), while small $a_{i,j}$ denotes dissimilarity. When $\mathcal{A}$ is the inverse of the covariance matrix, QF is equivalent to the Mahalanobis distance.

- **Quadratic-Chi (QChi) Distance** [18] : This cross-bin distance has a similar property as χ^2 distance that it reduces the effect of differences caused by bins with large values. It is defined by:

$$D_{QChi}(\mathbf{P}, \mathbf{Q}) = \sqrt{\sum_{ij} \left(\frac{(p_i - q_i)}{(\sum_c (p_c + q_c) a_{c,i})^m} \right) \left(\frac{(p_j - q_j)}{(\sum_c (p_c + q_c) a_{c,j})^m} \right) a_{i,j}} \tag{6}$$

  where $0 \leq m < 1$ is a normalization factor (m is set to 0.5 in this work), and $\mathcal{A}$ is a $n \times n$ similarity matrix.

- **Earth Mover's Distance (EMD)** : The EMD, proposed by Rubner et al. [19], is a cross-bin distance which defines the minimal amount of work to be performed to transform one histogram to other by moving distribution mass. It is defined as:

$$D_{EMD}(\mathbf{P}, \mathbf{Q}) = \min_{\mathcal{F}} \sum_{i=1}^n \sum_{j=1}^n f_{i,j} d_{i,j} \tag{7}$$

  subject to the following constraints:

$$f_{i,j} \geq 0, \quad \sum_{j=1}^n f_{i,j} = q_i, \quad \sum_{i=1}^n f_{i,j} = p_j \tag{8}$$

  where $f_{i,j}$ of a flow matrix $\mathcal{F}$ indicates flow to move from the i-th bin to the j-th bin, and $d_{i,j}$ of a ground distance matrix $\mathcal{D}$ represents the cost of moving flow from the i-th to the j-th bin.

3. PROPOSED HUE DIFFERENCE MEASURE

In this section, we develop a general processing pipeline to measure perceptual difference between two images using hue histogram descriptor. Hue is an attribute closely related to the dominant wavelength of color signal. It has the geometric interpretation in the chromaticity plane, as the angular value of the point measured around the achromatic axis, e.g. in $a^* - b^*$ plane of CIELAB space, hue is the angular position of the point measured from the positive a^* axis.

As demonstrated in Fig 1, the processing sequence is composed of following main components: i) image normalization, ii) histogram based difference computation. The inputs to the system are two RGB color images, $\mathbf{X}$ and $\mathbf{Y}$ ($\mathbf{X}, \mathbf{Y} : \mathbb{R}^2 \rightarrow \mathbb{R}^3$), which are assumed to be consistent in spatial resolution and bit depth, as well as properly aligned. The output of the system $CD_H(\mathbf{X}, \mathbf{Y}) \geq 0$ is a measure

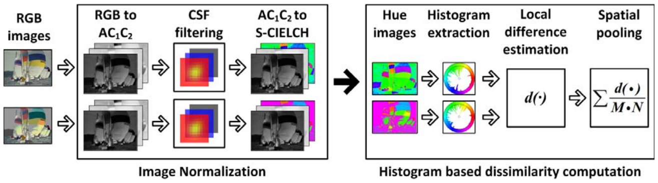

Fig. 1. Hue histogram descriptor based color difference prediction

of color difference between two images. Our metric translates input color signal to the perceptually uniform CIELAB, where hue component is accessible. A cross-bin histogram distance measure from Section 2 is applied to quantify the difference of hue distribution in local image patches $\mathbf{x}$ and $\mathbf{y}$. Adopting SSIM framework [3], pixel-by-pixel differences are estimated using a sliding window, then final score is derived by applying a spatial pooling.

3.1. Viewing Distance Normalization

Prior to extract hue component from input images, we exploit a pre-processor of spatial CIELAB (S-CIELAB) [20], which normalizes visual information based on observer's viewing distance by approximating the CSF of human visual system. The input RGB images are initially transformed to opponent color space AC_1C_2, where each channel component represents luminance, red-green, and blue-yellow information, respectively. Subsequently, each channel is spatially filtered using filters that approximate the CSF. Readers can refer to [20] for more detailed description of the CSF filters. Finally, filtered opponent space images are transformed to perceptually uniform CIELAB domain (resultant images are equivalent to S-CIELAB representation), and hue component H is extracted from two chromaticity components a^* and b^* by $H = \tan^{-1}(b^*/a^*)$.

3.2. Histogram based Difference Computation

As different image regions may exhibit different types of distortion, we measure hue difference within local regions. Given two corresponding local patches of hue images, $\mathbf{x}$ and $\mathbf{y}$ (assume that each local patch contains L pixels, i.e. $\mathbf{x} = \{x_i | i = 1, \ldots, L\}$, $\mathbf{y} = \{y_i | i = 1, \ldots, L\}$, the local hue difference term $CD_H(\mathbf{x}, \mathbf{y}) : \mathbb{R}^L \times \mathbb{R}^L \to \mathbb{R}$ is given by:

$$CD_H(\mathbf{x}, \mathbf{y}) = d(hist(\mathbf{x}), hist(\mathbf{y})) \tag{9}$$

where $d(\cdot)$ is a histogram distance measure. In our proposed scheme, we make use of the QF distance [17] for following reasons: i) it allows us to model the perceptual similarity/dissimilarity relationship between the hue values via the similarity matrix $\mathcal{A}$; ii) it is a computationally efficient cross-bin distance [18], and relatively insensitive to the quantization size than other bin-to-bin solutions [19].

For elements $a_{i,j}$ of the similarity matrix $\mathcal{A}$, we exploit a negative exponent function as follows:

$$a_{i,j} = 1 - \exp\left(-\alpha \times \frac{d_{i,j}}{d_{max}}\right) \tag{10}$$

where $d_{i,j} = \min(|i-j|, n - |i-j|)$ is ground distance between bins for modulo (circular) data, d_{max} is the maximum value of $d_{i,j}$, and α adjusts the relative importance between small and large hue differences (in this work, α is empirically set to 32). This function, adopted from [19], practically saturates large hue difference to a threshold. It is desirable in a sense that if human observers are asked to judge the perceived difference of hue far apart in hue wheel, they are likely unable to numerically quantify the difference rather than consider them totally different (Similarly, state-of-the-art color difference solution, CIEDE2000 [21], only holds true for a pair of color within small to medium distance in CIELAB space).

In order to derive a single score that represents overall perceived difference, individual local measurement are combined. By conducting a spatial pooling, hue difference score $CD_H(\mathbf{X}, \mathbf{Y}) : \mathbb{R}^{M \times N} \times \mathbb{R}^{M \times N} \to \mathbb{R}$ (M and N indicates the height and width of input images) is obtained by:

$$CD_H(\mathbf{X}, \mathbf{Y}) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} CD_H(\mathbf{x}_{i,j}, \mathbf{y}_{i,j}) \tag{11}$$

4. EXPERIMENTAL RESULTS

The main objective of the evaluation is to see if the metric is statistically consistent with visual perception, especially when the images are subject to degradation caused by color gamut mapping. The evaluation database, compiled by Lichtenauer et al. [22], includes images exhibiting perceptual degradation caused by color GMAs. This DB consists of a wide variety of reference color images, ranging from indoor to outdoor scenes, from natural scene to human subjects. From these reference images, gamut mapped images are generated using commonly used GMAs. This database is originated from four different studies, which are summarized in Table 1.

DB Name	N_R/N_T	F	R	G_C/G_{NC}	AHR
Basic Study	97 / 1067	8bit/ch TIFF	287x400 to 600x400	5199 / 5550	98.58%
Image Gamut	65 / 520	8bit/ch TIFF	267x400 to 653x400	3698 / 4087	84.67%
Local Contrast	72 / 576	8bit/ch TIFF	252x400 to 743x400	5209 / 5376	81.80%
Mix	86 / 1628	8bit/ch TIFF	333x500 to 720x480	26003 / 30563	75.15%
Total	320 / 3791	8bit/ch TIFF	252x400 to 720x480	40109 / 45576	79.92%

Table 1. Description of image databases in experiment (N_R/N_T: number of reference/test images; F: image format; R: image resolution; G_C/G_{NC}: groundtruth, i.e. number of paired comparisons/number of non-tied comparisons; AHR: achievable hit rate)

The validation of the proposed metric is carried out by quantifying how well the estimated score matches with observer's paired comparison results. They are generated through psycho-visual tests; given a reference image and two images altered by different GMAs, an observer chooses the one that reproduces the original scene closer. The comparison test allows tie when an observer could not decide which pair is preferred. Inheriting the evaluation protocol from [9], the performance is reported by the hit rate, defined as:

$$\text{Hit rate} = \frac{\text{Number of correctly predicted choice by score}}{\text{Number of non-tied paired comparisons}} \tag{12}$$

Theoretically, maximum achievable hit rate is less than 100% since observers made inconsistent votes even on the same image pairs, displayed under the same viewing condition [22].

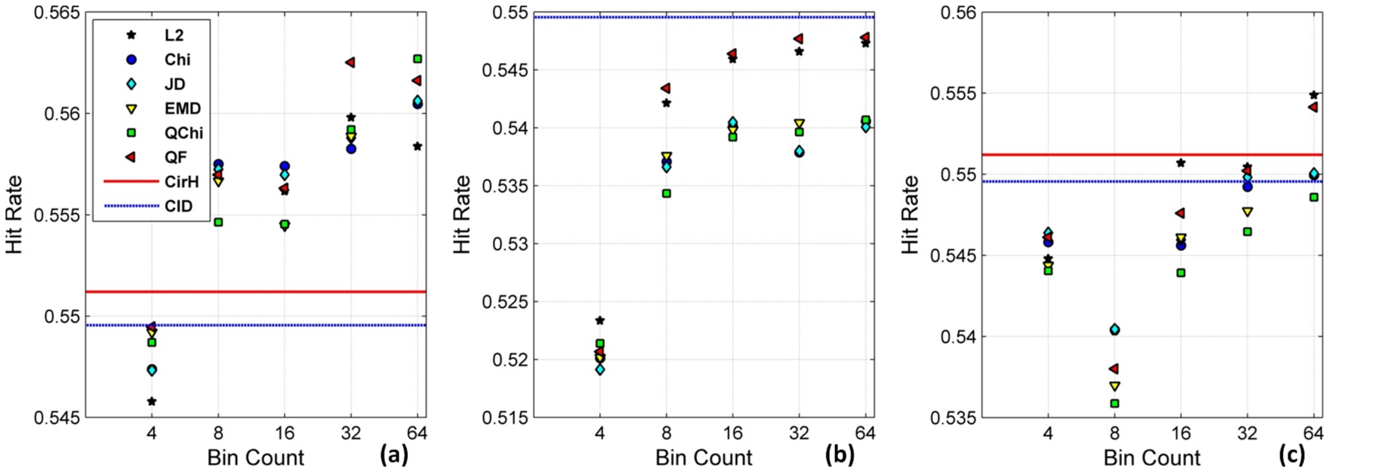

Fig. 2. Hit rate performance of various hue difference measures on gamut mapping DB extracted from three commonly used hue representations: (a) S-CIELAB, (b) CIELAB, (c) HSV

Fig 2 compares the hit rate performance of the proposed scheme along with various histogram distance functions, e.g. L_2, Chi, JD, QChi, and EMD distances (refer to Section 2.2), on experimental dataset. In order to investigate the performance dependency on the quantization level, hit rates for histogram based methods are measured with varying quantization levels of hue domain from 4 to 64 bins (For EMD, we test upto 32 bins due to its slow computation). We also include two other difference measures exploiting hue features in our comparisons: i) the hue direction comparison measure in [23] (denoted as CirH), ii) the hue comparison term from state of the art color difference metric by Lissner et al. [9] (denoted as CID). Aforementioned two methods rely on local mean information of hue values rather than local hue distribution.

To observe the influence of different hue representation on the performance, we derive hue values from three different color spaces: i) CIELAB with CSF filtering enabled, (denoted as S-CIELAB) ii) CIELAB without CSF filtering, iii) HSV [24], which is a close approximation of CIELAB. For our experiment, the image local patch size L in Section 3.2 is explicitly set to 11×11, adopting general practice of SSIM framework [3]. CSF filtering is performed based on the viewing condition of 40 pixels per degree [9].

The results indicate that CSF filtering is crucial in achieving optimal prediction as enabling it clearly yields enhanced hit rates over all combinations of distance functions and bin quantization sizes. This observation is consistent with other researches [9, 23, 25], where CSF filtering has proven to be a successful preprocessing module for color difference analysis. In fact, CIELAB itself is not as effective as its low-complexity alternative HSV, since it results in slightly worse hit rate performance in the absence of CSF filtering.

Hue histogram descriptor based solutions consistently outperform two benchmark solutions, CirH and CID, demonstrating the effectiveness of hue distribution information over simple mean value of hue in difference assessment. In all three hue representations, the most coarse bin size (4 bin) yields suboptimal outcomes, and hit rates generally increase as finer quantization is used. However, there is a tradeoff between computational delay and performance gain since finer quantization leads to larger dimensional vectors for histogram descriptor. The best hit rate of 56.27% is achieved when QChi distance is used with 64 bins in S-CIELAB. However, QF distance is less sensitive to bin size selection, while consistently maintaining high hit rate over wide range of quantization sizes in all three color spaces (best hit rate for QF is 56.25% with 32 bins in S-CIELAB). Hence, it justifies the use of QF distance in our proposed metric. We believe there is further room for improvement, by fine tuning a similarity matrix $\mathcal{A}$ of QF distance. Fig 3 visually demonstrates the effectiveness of the proposed scheme on dealing with difference types of chromatic distortions.

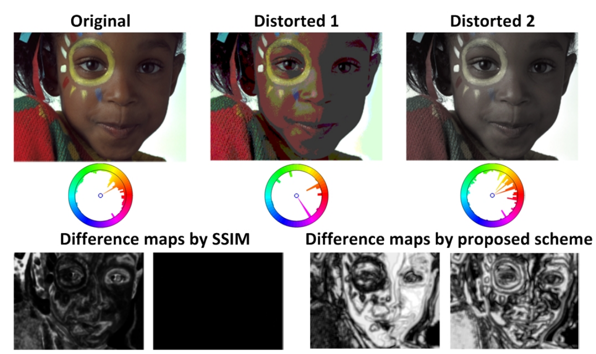

Fig. 3. Sample images with two types of chromatic distortions taken from TID2013 DB [26] and difference maps obtained by SSIM [3] and the proposed measure. (lighter pixels indicate high dissimilarity)

5. CONCLUSION

In this paper, we have introduced a perceptual color difference measure, exploiting hue histogram descriptors. The proposed full-reference difference predictor extracts hue attributes from a pair of color images to be compared and quantifies their perceptual difference based on hue distribution of corresponding local regions. To achieve good correlation between subjective assessment score and the proposed scheme, we make use of CSF filtering, as well as highly perceptual cross-bin histogram distance functions. Experimentation, performed on color images exhibiting visual degradation caused by gamut mapping process, indicates the effectiveness of the proposed metric against chromatic distortions, making it useful for optimization of color gamut mapping applications.

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