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Chroma and Contrast Features Based Image Difference Measure in Various Scales

S. Abitha[1], T. Kavitha[2]
[1]*Student,* [2]*Assistant Professor, Department of Computer Science and Engineering, Regional Centre of Anna University Tirunelveli (T.N) India*
[1]abitha_noor@yahoo.co.in
[2] kavi_gce@rediffmail.com

***Abstract*— An image difference structure is created that include of image regularization, feature derivation, and feature grouping. Based on this structure image difference measure is created by selecting exact implementations for each of the steps. An image difference prediction is then calculated using image difference features (IDFs) that are derived from the images. The input images are then regularized with an image appearance model and are changed into a working color space. Difference map are calculated by Lightness, Chroma , Hue , Lightness-Contrast, Lightness-Structure and Chroma-Contrast comparisons within the working color space. Along with this different Scale wise are analysed for image difference measure. Each map is finally transformed into a characteristic value calculation that is the mean value of all pixels. The resulting IDFs are grouped into an image-difference measure (IDM) to predict distortion.**

***Keywords*— Image Difference features(IDFs),Image Difference Measure (IDM),Working color space, Image appearance model, Difference map, Characteristics value computation.**

I. Introduction

Image-appearance modeling is still in its immaturity. For example, the contrast-sensitivity method is regularly modeled as a complexity in an intensity-linear opponent color space. Various filters are applied to the achromatic and chromatic channels in the occurrence area[1] .

Image quality estimation is basic to the presentation optimization of imaging systems including the capture, display, storage, and transmission of images. Quality estimation is intimately related to human sensitivity. A quality metric is considered correct if its results are dependable with the subjective calculation. To calculate the metric performance, subjectively-rated databases are used as “ground truths”. Generally, the destruction, such as blocking artifacts, blur, additive noise, etc., are frequently involved in real-world applications. The databases present the reference images, the distorted images, and the subjectively-rated scores of the distorted images[2].

In this paper, a new image database, TID2008, for evaluation of full-reference visual quality assessment metrics is described. It contains 1700 test images (25 reference images, 17 types of distortions for each reference image, 4 different levels of each type of distortion)[3].

Objective image quality assessment research aims to design qual- ity measures that can automatically predict perceived image qual- ity. These quality measures play important roles in a broad range of applications such as image acquisition, compression, commu- nication, restoration, enhancement, analysis, display, printing and watermarking. The most widely used full-reference image quality and distortion assessment algorithms are peak signal-to-noise ra- tio (PSNR) and mean squared error (MSE), which do not correlate well with perceived quality[4].

In recent years, there has been an increasing interest in developing objective image quality assessment (IQA) methods that can automatically predict human behaviors in evaluating image quality [5]. Such perceptual IQA mea- sures have broad applications in the evaluation, control, design and optimization of image acquisition, communication, pro- cessing and display systems. Depending upon the availability of a “perfect quality” reference image, they may be classified into full-reference (FR, where the reference image is fully accessible when evaluating the distorted image), reduced-refer- ence (RR, where only partial information about the referenceimage is available) and no-reference (NR, where no access to the reference image is allowed) algorithms [3].

A. Prediction

The image difference structure present in this paper normalizes the input images with an image appearance model and transforms them into a working color space. An image difference prediction is then computed using image difference features (IDFs) that are extracted from the images.

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The analysis of an image by the visual system depends on the viewing situation, e.g., viewing distance, illuminant, and luminance level. accordingly, the images should be normalized to specific viewing conditions before any information is extracted. So image-appearance models have been developed for this purpose. Among the mechanisms that they model are chromatic adaptations, contrast sensitivity.

In the final step of the normalization process, the images are transformed into a working color space. This color space should present simple admittance to color attributes lightness, chroma, and hue and it should be free of cross- contamination between these attributes. One of the most important properties is perceptual equality, meaning that Euclidean distances in the space match perceived color differences. This is required for an perfect demonstration of image features such as edges and gradients. In an RGB color space, such features may be over- or underestimated, i.e., their computed magnitudes go beyond their professed magnitudes or vice versa.

The image difference features (IDFs) from the normalized input images is extracted. These features are arithmetical formulations of hypotheses on the visual processing. They are combined into an overall image-difference calculation using a grouping model. The parameters of this model are optimized using image-difference datasets.

II. Related Work

A. Image Difference Prediction

In digital image reproduction it is often desirable to compute image difference of reproductions and the original images. The traditional CIE color difference formula, designed for simple color patches in controlled viewing conditions. This paper introduced the S-CIELAB model to account for complex color stimuli using spatial filtering as a preprocessing stage. Building on S-CIELAB, iCAM was designed to serve as both a color appearance model . Once in the opponent space, the images are filtered with approximations of human contrast sensitivity functions (CSFs) to remove information that is invisible to the human visual system. The images are then transformed back to a color difference space such as CIELAB, and pixel-by-pixel color differences are calculated.

MSE predicts quality of white noise distorted image well, but fails to cope with other distortion types and cross artifacts measurement.

Seeking the substitutes for the MSE, the researchers have paid a lot of attention to the properties of the human visual system (HVS). The distortions being decomposed into the frequency subbands (e.g., discrete cosine transform coefficients) still have highorder correlations and interaction with each other) the high- order Minkowski norm is regarded as a better pooling strategy than the Euclidean norm a lot of factors need to be determined so as to accurately simulate the cases of diverse display media, varying illumination conditions, and different viewing distances. Due to these reasons , the HVS based metrics are often complicated and difficult to optimize, and cannot guide the application effectively[7].

Using S-CIELAB as a show, a modular structure for the development of color image difference models has been described. The first component began with the easy S-CIELAB contrast sensitivity functions and was enlarged with more accurate filters, as well as a method for improving image differences where the human visual system is most perceptive. A simple procedure for accounting for localization using edge improving filters was then introduced. Methods for contrast improvement, direction, covering, and data decrease were also discussed. The goal of this structure is to create a possible metric of image reliability. This metric can be used to test the output of different imaging systems. The eventual goal from this work is to create a groundwork for a model of image quality that can calculate both

Colour difference measures are mostly based on nearly equal, homogeneous, structureless patches on an achromatic background , image difference measures have to take the spatially changing nature of the stimuli into account.It first consider the performance of two image similarity measures. A fundamental, luminance only description of SSIM was match up to a colour image difference measure (CID) joining contrast sensitivity filtering, SSIM features and chromatic characters. For the performance the principal objective was to compare observation of distortions on abstract and usual images. Used artificial distortions, since chromatic distortions in gamut mapping often lean to be related in luminance and chroma[9].

The structural similarity image quality method is based on the hypothesis that the human visual system is highly personalized for extracting structural information from the view, and consequently a measure of structural similarity can present a better estimate to professed image quality.

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It recommend a multi scale structural similarity method, which supplies more flexibility than exiting single scale concepts in including the differences of viewing conditions. To expand an image separation method to standardize the parameters that define the relative importance of different scales[10].

III. PROPOSED SYSTEM

First to choose two input images where one is the reference image and another one is the distorted image. The given two input images are converted from RGB to XYZ color space. The purpose of converting from RGB to XYZ is that the illuminance will be very effective in XYZ than in RGB. The XYZ color space images are converted to its respective CSF filter. The purpose of CSF Filter is that it does not affect the contrast of the images. The above two methods are called Image Appearance Model. The CSF filter images are converted into CIELAB color space. This CIELAB color space is the working color space. Image difference predictions are done on this working color space. The difference map is calculated using Lightness, Chroma , Hue , Lightness-Contrast , Lightness-Structure and Chroma-Contrast Comparisons. Finally the image difference prediction is calculated using IDM .

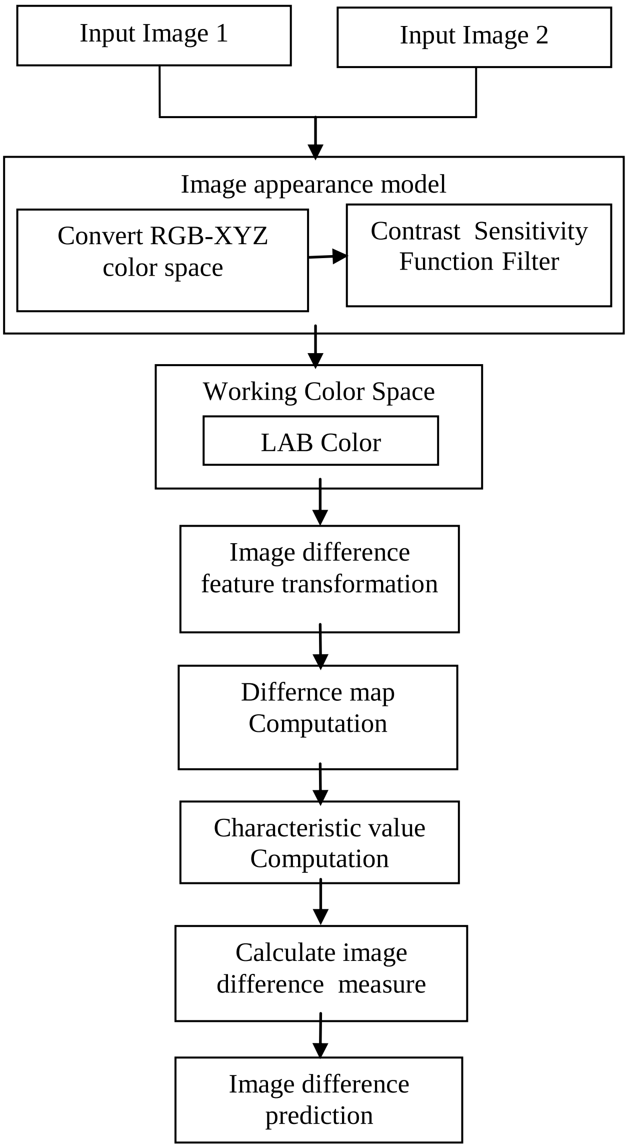

Fig.1 System Architecture

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A. Image Difference Feature (IDF)

As a first step of IDF calculation an image appearance model is used to normalize the input images to the exact viewing conditions (illuminant, luminance level, and viewing distance).The input images are then transformed into a working colour space with sure valuable assets for occurrence, Euclidean distances in this space should closely match perceived colour differences. This certifies that image features, such as edges and gradients, are judged correctly by the consequent feature extraction schedules.

Image-difference features are computed as follows:

1. Role of Image Appearance Model

The analysis of an image by the visual system depends on the viewing situation , e.g., observation distance, illuminant, and luminance stage. Accordingly, the images should be normalized to exact viewing conditions before any information is derived. So image appearance models have been developed for this reason. Among the methods that they model are chromatic adaptation, contrast sensitivity, and differents appearance occurrence. Image appearance methods can increase the prediction performance of image difference measures.

2. Role of Working Color Space

The images converted into a working color space. This color space should present simple access to color features lightness, chroma, and hue.This is needed for an accurate representation of image features such as edges and gradients. Choose the LAB2000HL color space as working color space, because it was designed to satisfy the needs. The color space has a lightness axis ”L”, a red-green axis ”a” and a blue-yellow axis ” b”.

3. Role of Difference map generation

Maps are produced that replicate differences between the images, e.g., gradient differences or color differences.Difference map are computed by Lightness , Chroma , Hue , Lightness Contrast , Lightness Structure and Chroma Contrast Comparisons

4. Role of Characteristic-value computation

Each map is finally converted into a characteristic value computation , e.g., the mean value of all pixels.

B. Image-Comparison Transformations

Three comparison terms are evaluated independently and then multiplied is well matched for image difference structure .The arguments x and y are the pixel arrays in the working color space, each pixel x consists of a lightness and two chromatic values

$$x = (L_x, a_x, b_x) \quad (1)$$

The chroma of the pixel is defined as

$$C_x = \sqrt{{a_x}^2 + {b_x}^2} \quad (2)$$

1. Lightness, chroma, and hue comparisons:

$$l_L(x,y) = \frac{1}{c1.\,\Delta L(x,y)^2 + 1} \quad (3)$$

$$l_C(x,y) = \frac{1}{c4.\,\Delta C(x,y)^2 + 1} \quad (4)$$

$$l_H(x,y) = \frac{1}{c5.\,\overline{\Delta H(x,y)}^2 + 1} \quad (5)$$

2. Pixel-wise Transformations

The pixel wise transformations used above are defined as:

$$\Delta L(x, y) = L_x - L_y \quad (6)$$

$$\Delta C(x, y) = c_x - c_Y \quad (7)$$

$$\Delta H(x, y) = \sqrt{(a_x - a_y)^2 + (b_x - b_y)^2 - \Delta C(x,y)^2} \quad (8)$$

These terms are based upon the suggestions that the HVS is perceptive to lightness, chroma, and hue differences. Their structure is extracted from the luminance purpose of the SSIM index. It is changed into our perceptually homogeneous working space.

3. Lightness-Contrast Comparision

$$C_L(x,y) = \frac{2\sigma_x\sigma_y + C2}{\sigma_x^2 + \sigma_y^2 + C2} \quad (9)$$

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Where σ_x and σ_y are the standard deviations of the lightness Components .The term reproduces the visual system's sensitivity to achromatic contrast differences and it's called contrast covering possessions. The impact of this property is modeled by adjusting the parameter c2 to the working color space.

4. Lightness-Structure Comparison

$$S_L(x,y) = \frac{\sigma_{xy}+C3}{\sigma_x\sigma_y+C3} \quad (10)$$

Where σ_{xy} corresponds to the cosine of the angle between $x-\bar{x}$ and $y-\bar{y}$ in the lightness component. The term incorporates the assumption that the HVS is sensitive to achromatic structural differences.

5. Chroma-Contrast Comparison

$$C_{Cont}(x,y) = \frac{2\rho_x\rho_y+C6}{\rho_x^2+\rho_y^2+C6} \quad (11)$$

Where ρ_x and ρ_y are the standard deviations of the chromatic Components .

Where

C1	C2	C3	C4	C5	C6
0.002	0.1	0.1	0.002	0.008	0.1

$\alpha1$	$\alpha2$	$\alpha3$	$\alpha4$	$\alpha5$
0.0448	0.2856	0.3001	0.2363	0.1333

C. Image Difference Measure

Image difference measure (IDM) is a transformation that combines several IDFs to predict image differences .It has the same structure as an IDF . All IDFs that are combined into an IDM share the same normalization transformation N.

$$\text{IDM}= 1 - (L_L^n)^{an} \cdot \prod_{i=1}^{n}\left(C_L^i S_L^i\right)^{\alpha i} . L_C \cdot L_H \cdot C_{Cont} \quad (12)$$

Where n is the number of scales used by the multiscale model, L_L^n is the lightness comparison IDF on the n-th (smallest) scale. C_L^i and S_L^i are the lightness-contrast and lightness- structure IDFs on the i-th scale, and αi is the weight of this scale.The α_i weight the contribution of each scale to the overall image-difference prediction The product of all scales is a weighted geometric mean, i.e.,

$$\sum \alpha_i = 1$$

IV. Simulation And Results

First to choose two input images where one is the reference image and another one is the distorted image. The given two input images are converted from RGB to XYZ color space. The purpose of converting from RGB to XYZ is that the illuminance will be very effective in XYZ than in RGB. The XYZ color space images are converted to its respective CSF filter. The purpose of CSF Filter is that it does not affect the contrast of the images. The above two methods are called Image Appearance Model. The CSF filter images are converted into CIELAB color space. This CIELAB color space is the working color space. Image difference predictions are done on this working color space. The difference map is calculated using Lightness, Chroma , Hue , Lightness-Contrast and Lightness-Structure Comparisons. Finally the image difference prediction is calculated using IDM .

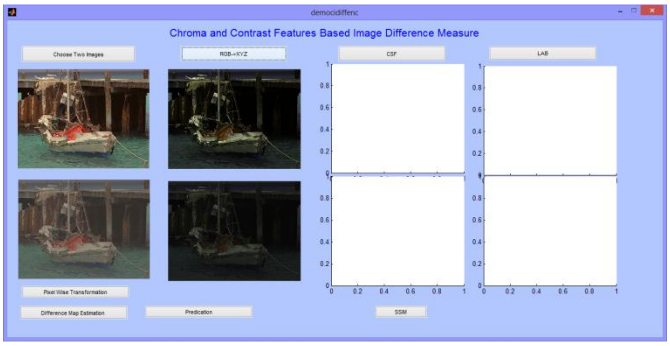

Fig.2 Convert RGB to XYZ color space

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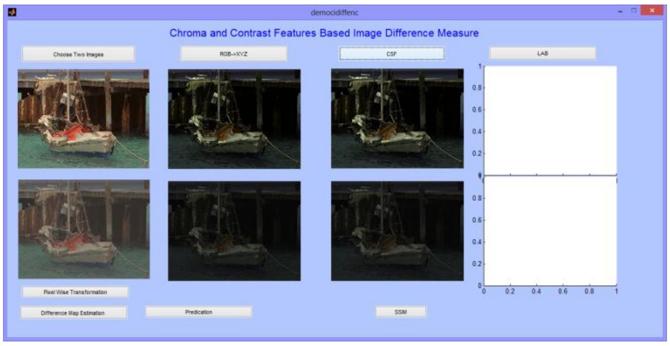

Fig. 3 CSF filter images

Fig.4 Working color space

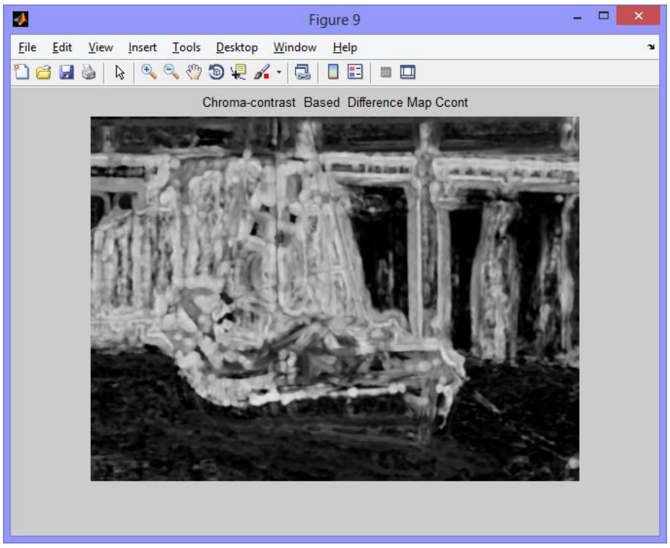

Fig.5 Chroma-Contrast Based Difference Map

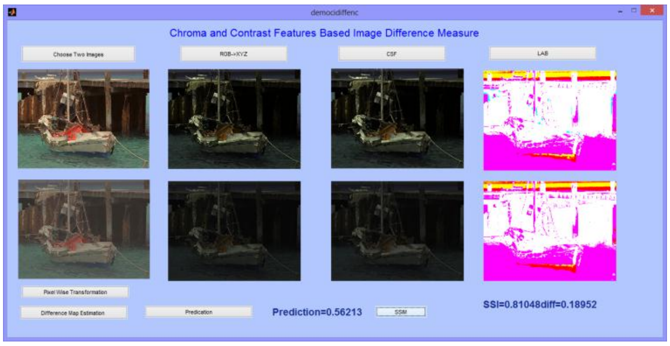

Fig.6 comparison of IDM with SSIM value

The IDM prediction outcome is compared with SSIM value.

As a result the IDM predicted outcome value is greater than the SSIM value

A. *Comparative Analysis on Prediction Rate*

The result of the proposed method Image Difference Measure is compare to the existing method result SSIM. The comparison result shows that the proposed method Image Difference Measure yields high accurate prediction than the existing method SSIM. Table 1 shows the proposed method Image Difference Prediction value and existing method value for each five sample images.

Table 1
Performance comparison based on the Choma&Contrast based IDM Prediction and SSIM

Image	Chroma&Contrast IDM Prediction	SSIM
House	0.25069	0.037068
Women	0.76505	0.33139
Boat	0.56213	0.18952
Light House	0.59177	0.40484
Bird	0.55645	0.088027

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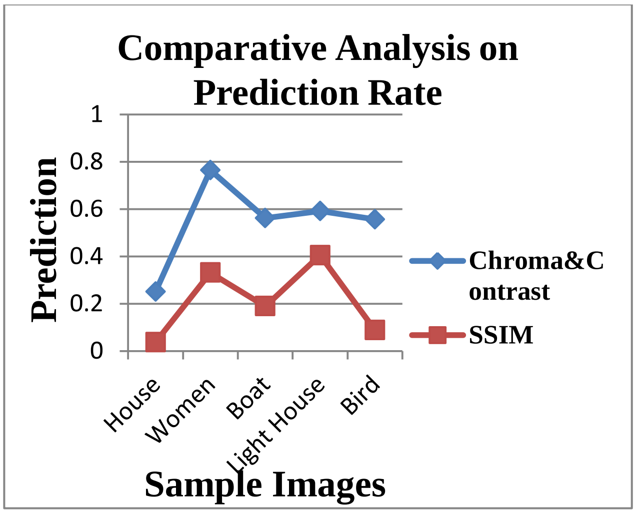

Fig.7 Performance comparison based on the Chroma&Contrast IDM Prediction and SSIM

Fig.7 shows that the proposed method Image Difference Measure yields high accurate prediction than the existing method SSIM.

The Different Scale Wise are analysed as follows.

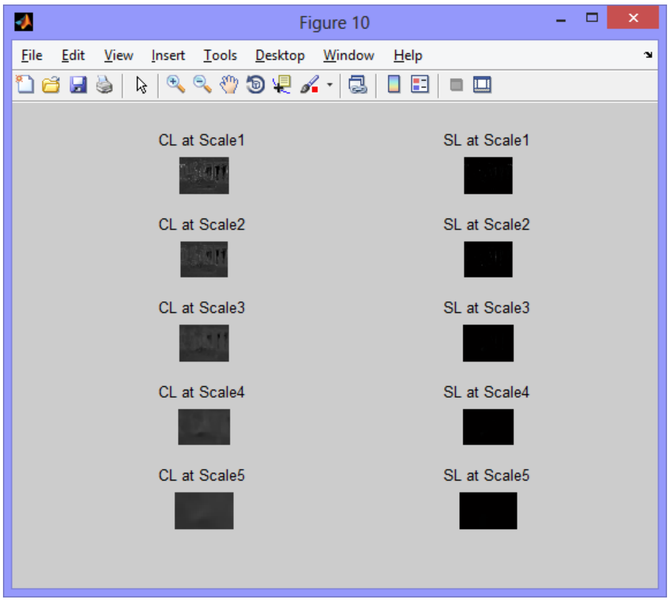

Fig.8 Different Scale wise Analysis

Table.2
Different Scale wise Analysis on IDM-CRCONT Prediction

Image	Scale value	IDM-CRCONT
Boat	1	1
Boat	2	0.61015
Boat	3	0.5903
Boat	4	0.57467
Boat	5	0.56213

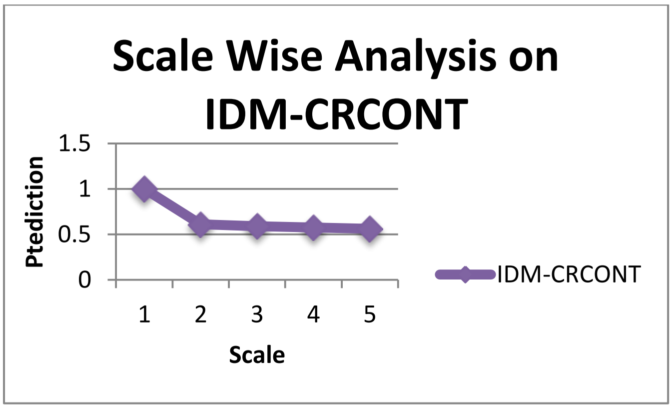

Fig.9 Different Scale Wise Analysis on IDM-CRCONT Prediction

V. Conclusions

The framework for the assessment of perceived image differences is presented. It normalizes the images to specific viewing conditions with an image appearance model, extracts image- difference features (IDFs) that are based upon hypotheses on perceptually important distortions, and combines them into an overall image difference prediction. Particular emphasis was placed on color distortions, especially those resulting from gamut mapping transformations.

The image difference measures (IDMs) based on this framework using IDFs adopted from the terms of the SSIM index is created. They are numerical representations of assumptions about perceptually important achromatic and chromatic distortions.

The most important conclusion is that adding a chroma or hue based IDF (or both) significantly improves the predictions on the gamut-mapping data. This illustrates the benefit of including color information into image difference measures.

REFEENCES

[1] Ingmar Lissner, Jens Preiss, Philipp Urban, Matthias Scheller Lichtenauer, and Peter Zolliker "Image-Difference Prediction: From Grayscale to Color"

[2] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," IEEE Trans. Image Process., vol. 13, no. 4, pp. 600–612, Apr. 2004.

[3] Z. Wang, E. P. Simoncelli, and A. C. Bovik, "Multiscale structural similarity for image quality assessment," in Proc. IEEE 37th Asilomar Conf. Signals, Syst. Comput., vol. 2. Pacific Grove, CA, Nov. 2003, pp. 1398–1402.

[4] H. R. Sheikh, M. F. Sabir, and A. C. Bovik, "A statistical evaluation of recent full reference image quality assessment algorithms," IEEE Trans. Image Process., vol. 15, no. 11, pp. 3440–3451, Nov. 2006.

[5] J. Morovicˇ, Color Gamut Mapping. Chichester, U.K.: Wiley, 2008.

[6] E. Reinhard, G. Ward, S. Pattanaik, and P. Debevec, High Dynamic Range Imaging: Acquisition, Display, and Image-Based Lighting, 1st ed. San Francisco, CA: Morgan Kaufmann, 2006.

[7] Z. Wang and Q. Li, "Information content weighting for perceptual -image quality assessment," IEEE Trans. Image Process., vol. 20, no. 5, pp. 1185–1198, May 2011.

[8] J. Preiss, I. Lissner, P. Urban, M. Scheller Lichtenauer, and P. Zolliker, "The impact of image-difference features on perceived image differences," in Proc. 6th Eur. Conf. Color Graph., Imag., Vis., Amsterdam, The Netherlands, 2012, pp. 43–48.

[9] M. Scheller Lichtenauer, P. Zolliker, I. Lissner, J. Preiss, and P. Urban, "Learning image similarity measures from choice data," in Proc. 6th Eur.Conf. Color Graph., Imag., Vis., Amsterdam, The Netherlands, 2012,

[10] N. Bonnier, F. Schmitt, H. Brettel, and S. Berche, "Evaluation of spatial gamut mapping algorithms," in Proc. 14th Color Imag. Conf., Scottsdale, AZ, 2006, pp. 56–61.