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Colour Conversion from Gray to RGB for Predicting Image Differences

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***Abstract*:** The prediction performance of existing methods is limited because the visual mechanisms responsible for assessing image differences are not well understood. Under the assumption that human visual perception is highly adapted for extracting structural information from a scene, this paper introduces a flexible framework for quality assessment based on the degradation of structural information. Based upon this concept, a Structural Similarity Index [SSIM] has been developed. Pair of input images is first normalized to specific viewing conditions by an image appearance model. Various image-difference features (IDFs) are then extracted from the images. These features represent assumptions about visual mechanisms that are responsible for judging image differences. Several IDFs are combined in a blending step to optimize the correlation between image-difference predictions and corresponding human assessments.

Keywords*-Structural Similarity Index(SSIM), Image Difference Measure(IDM), Image Difference Features(IDFs).*

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I. INTRODUCTION

The prediction accuracy of the multiscale SSIM index [3] on the LIVE database [4]: the Spearman correlation between subjective quality assessments and corresponding predictions is greater than 0.95 for all included distortions (lossy compression, noise, blur, and channel fading). Colour information is not required to predict these distortions since SSIM index works on grayscale data.

There are two things one should know about image quality assessment.

1. Lightness component may be unaffected by changes in chromatic components such as hue and chroma. It is frequently found in gamut-mapping [5] and tone-mapping [6] applications.
2. Changes of image semantics cannot be detected. For example if a distortion affects a human face in a portrait, the subjective image quality is considerably reduced. There are several extensions of the SSIM index for color images have been proposed [10], [11]. This paper believes that further improvements are possible.

In this work an image-difference framework that comprises image normalization, feature extraction, and feature combination is presented. Based on this framework, image-difference measures are created by selecting specific implementations for each of the steps. In this paper the color-related aspects of image-difference assessments are addressed. Here a best image-difference measure shows significantly higher prediction accuracy on a gamut-mapping dataset than all other evaluated measures. It focuses on full-reference measures, which predict the perceived difference of two input images. There are many such measures have been proposed [3], [12]–[17] other than SSIM index in the literature. Ideally, they reflect the actual visual mechanisms responsible for image-difference assessment. These mechanisms are poorly understood. Hypotheses on which information is extracted [2], [18] and how it is weighted and combined [7] can be found in the literature.

II. PROPOSED WORK

This image-difference framework consists of image normalization, feature extraction, and feature combination. An overview of this work is given in figure 1.

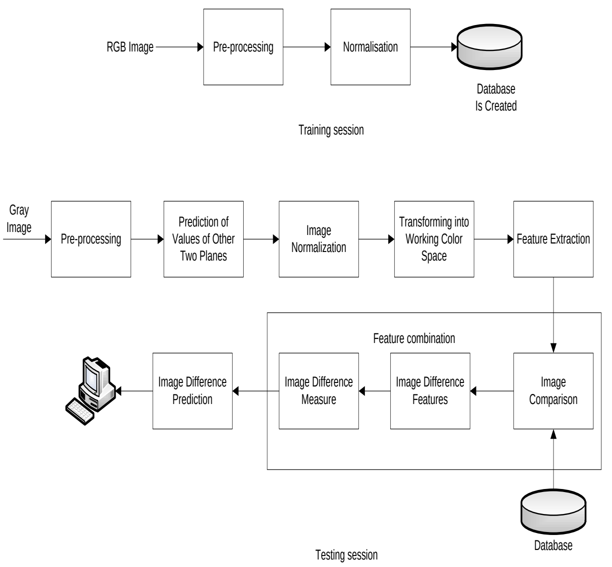


Figure 1. Block diagram

An image-difference framework that comprises image normalization, feature extraction, and feature combination is presented here. Based on this framework, image-difference measures are created by selecting specific implementations for each of the steps. Particular emphasis is placed on using color information to improve the assessment of gamut-mapped images. This image-difference measure shows significantly higher prediction accuracy on a gamut-mapping dataset than all other evaluated measures.

The whole process takes place in two sessions. First is the training session in which an RGB image is converted into gray scale image and the appropriate dataset is extracted. Next is the testing session in which the gray image is converted back into RGB image.

This work addresses the color-related aspects of image difference assessment. There is a focus on full-reference measures, which predict the perceived difference of two input images. Assumptions are made about how the human visual system (HVS) extracts and processes image information.

A. Image normalization

The interpretation of an image by the visual system depends on the viewing conditions, e.g., viewing distance, illuminant, and luminance level. Therefore the images should be normalized to specific viewing conditions before any information is extracted. Image-appearance models have been developed for this purpose. Here three image appearance models are used namely HSV, LAB, and YCbCr. In the final step of the normalization process, the images are transformed into a working color space. This color space should provide simple access to color attributes.

B. Feature extraction

Image-difference features (IDFs) are extracted from the normalized input images. These features are mathematical formulations of hypotheses on the visual processing.

An image-difference feature (IDF) is a transformation

$$IDF: I_{M,N} \times I_{M,N} \times P \rightarrow [0, 1] \quad (1)$$

Where, $I_{M,N}$ is the set of all colorimetrically specified RGB images with M rows and N columns; P is a set of parameter arrays. P may include the viewing distance, the luminance level, and the adaptation state of the observer depending on the model.

An IDF may be expressed as the concatenation of a transformation F that expresses the actual feature extraction and a transformation N that normalizes the images to the viewing conditions, i.e.,

$$IDF = F \circ N \quad (2)$$

Where $N: I_{M,N} \times I_{M,N} \times P \rightarrow W_{M,N} \times W_{M,N}$ (3)

$$F: W_{M,N} \times W_{M,N} \rightarrow [0, 1] \quad (4)$$

and $W_{M,N}$ is the set of images in the working color space with M rows and N columns. The feature-extraction transformation F used in this project is based upon a specific image-comparison transformation

$$t: W_{k,k} \times W_{k,k} \rightarrow [0, 1] \quad (5)$$

which compares pixels within corresponding k × k windows (k<< min{ M , N }) of the input images. The feature-extraction transformation F is computed by averaging the local differences as follows:

$$F(X_{norm}, Y_{norm}) = \sum_{i=1}^{k} t(x_i, y_i) \quad (6)$$

Where, k is the number of considered windows within the normalized images $X_{norm}, Y_{norm} \in W_{M,N}$ and x_i and y_i are the corresponding pixel arrays defined by the i^{th} window.

In this paper though mean of the difference maps is computed, more complex pooling methods may be in better agreement with human perception. Wang and Li [7] provided a comprehensive analysis. Scale-dependent IDFs include a transformation that extracts a specific image scale:

$$S : W_{M,N} \times W_{M,N} \rightarrow W_{'M,N} \times W_{'M,'N} \quad (7)$$

Where, M ≤ M and N ≤ N. The IDF that operates on this scale is defined by concatenation:

$$IDF = F \circ S \circ N \quad (8)$$

Where, F is adjusted to the scale defined by S.

C. Images-comparison transformations

This work utilizes established terms to ensure high prediction accuracy which describes image-difference features. These terms are adjusted to this framework and are extended to assess chromatic distortions. All terms are either adopted or derived from the SSIM index [2] due to its wide use and good prediction accuracy on various image distortions. In addition, three comparison terms are evaluated separately and then multiplied which is well suited for this image-difference framework. X and Y are the two compared images. The terms are computed within sliding windows in the compared images. Within these windows x and y are the pixel arrays. In the working color space, each pixel x consists of lightness and two chromatic values:

$x = (L_x, a_x, b_x)$. The chroma of the pixel is defined as

$$C_x = \sqrt{a_x^2 + b_x^2}.$$

1. Lightness, chroma, and hue comparisons:

$$I_L(x, y) = \frac{1}{c1 * \overline{f(x,y)} + 1} \quad (9)$$

$$I_C(x, y) = \frac{1}{c4 * \overline{f(x,y)} + 1} \quad (10)$$

$$I_H(x, y) = \frac{1}{c5 * \overline{f(x,y)} + 1} \quad (11)$$

where, $\overline{f(x,y)}$ indicates the Gaussian-weighted mean of $f(x, y)$ computed for each pixel pair (x, y) in the window and

$\overline{f(x,y)} = (\Delta L(x, y))^2$ in equation (9),

$\overline{f(x,y)} = (\Delta C(x, y))^2$ in equation (10) and

$\overline{f(x,y)} = (\Delta H(x, y))^2$ in equation (11).

The pixel-wise transformations used above are defined as:

$$\Delta L(x, y) = L_x - L_y \quad (12)$$

$$\Delta C(x, y) = C_x - C_y \quad (13)$$

$$\Delta H(x,y) = \sqrt{(a_x - a_y)^2 + (b_x - b_y)^2 - \Delta C(x, y)^2} \quad (14).$$

The above terms are based upon the hypothesis that the HVS is sensitive to lightness, chroma, and hue differences. Their structure is derived from the luminance function of the SSIM index [2], which is designed for an intensity-linear space. The terms L, C, and H are chosen such that they return similar results for similar perceived differences in a perceptually uniform color space and this applies only to small color differences. But the chroma differences for gamut-mapped images, to the original are usually quite large.

Using parameter C_i large color differences can be adjusted. The term H defined in (14) is a Euclidean rather than a hue-angle difference. It is required because the perceived hue difference of colors increases with chroma if their hue-angle difference stays constant. This is also used to adjust the scaling of hue differences to that of lightness and chroma differences in a perceptually uniform color space.

2) Lightness-contrast comparison according to [2]:

$$c_L(x, y) = (2\sigma_x\sigma_y + c_2)/(\sigma_x^2 + \sigma_y^2 + c_2) \quad (15)$$

where, σ_x and σ_y denotes the standard deviations of the lightness components in the sliding windows. It reflects the visual system's sensitivity to achromatic contrast differences and contrast-masking property by adjusting the parameter c_2 to the working color space the impact of this property is modelled.

3) Lightness-structure comparison according to [2]:

$$s_L(x, y) = (\sigma_{xy} + c_3)/(\sigma_x\sigma_y + c_3) \quad (16)$$

where, σ_{xy} corresponds to the cosine of the angle between

$x - \bar{x}$ and $y - \bar{y}$ [2] in the lightness component. This term incorporates the assumption that the HVS is sensitive to achromatic structural differences. Computing the terms in (9), (10), (11), (15), and (16) for sliding windows within the images X and Y results in five difference maps.

D. Resulting image-difference features

As shown in (2) and (6) each comparison term is incorporated into an individual IDF. L, C, and S are used to distinguish between terms and IDFs to denote the IDFs based upon the l -, c -, and s -terms.

The visual system is more sensitive to high-frequency distortions in the lightness component than in the chromatic components. Therefore, we create three lightness-based IDFs using the l_L -term shown in (9) and the terms from (15) and (16), c_L and s_L.

The visual system's response to differences in contrast and structure varies between scales [3] therefore the lightness-contrast and lightness-structure IDFs c_L and s_L are computed on several scales. On the first scale, the unaltered input images are used. These input images are then lowpass-filtered and downsampled by a factor of two to determine the images for the next smaller scale.

E. Image-difference measure

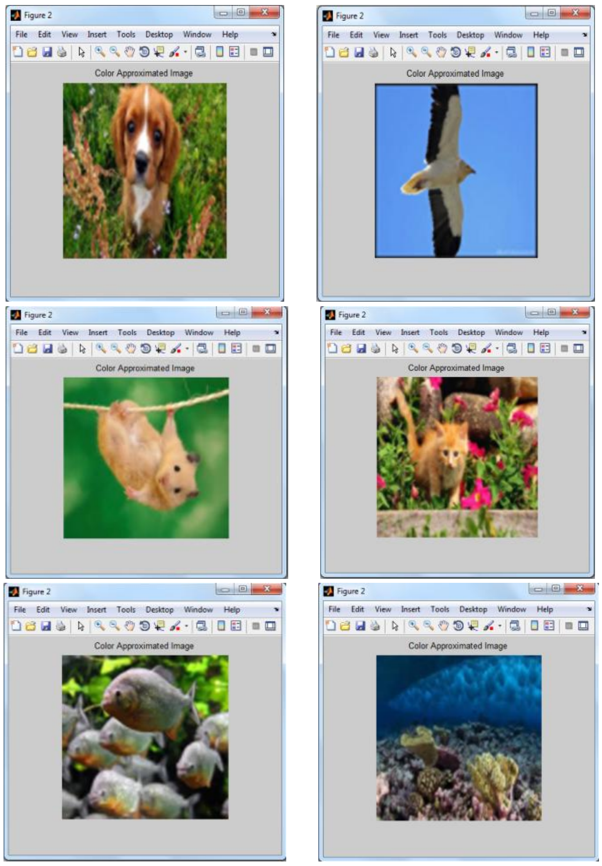
An image-difference measure (IDM) is a transformation that combines several IDFs to predict image differences which has the same structure as an IDF. All IDFs that are combined into an IDM share the same normalization transformation N. Here PSNR is used to measure image quality. It is measured in decibels (dB).

III. RESULTS AND CONCLUSION

A. Results

Figure 2. Set of input colour images

Figure 2 shows the set of input colour images considered in this project. These images are trained and a database is created by converting them to gray images. These gray images features are extracted and colour approximated images are created as shown in figure 3. Now the input images and colour approximated images are compared to predict the accuracy of image difference measure in terms of PSNR. Figure 4 shows PSNR values of each image considered in the experiment.



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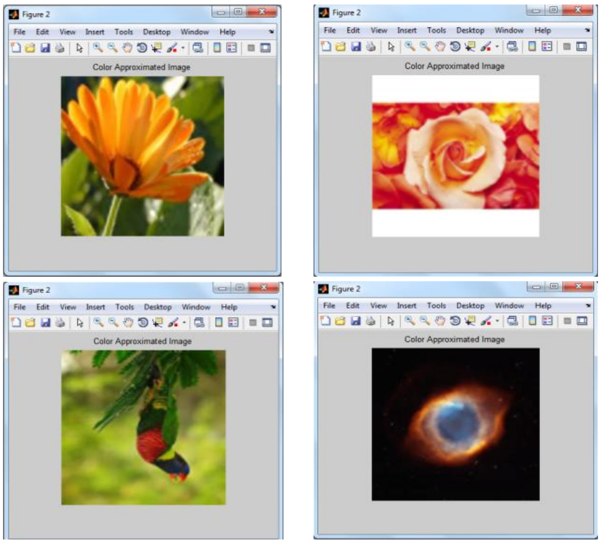
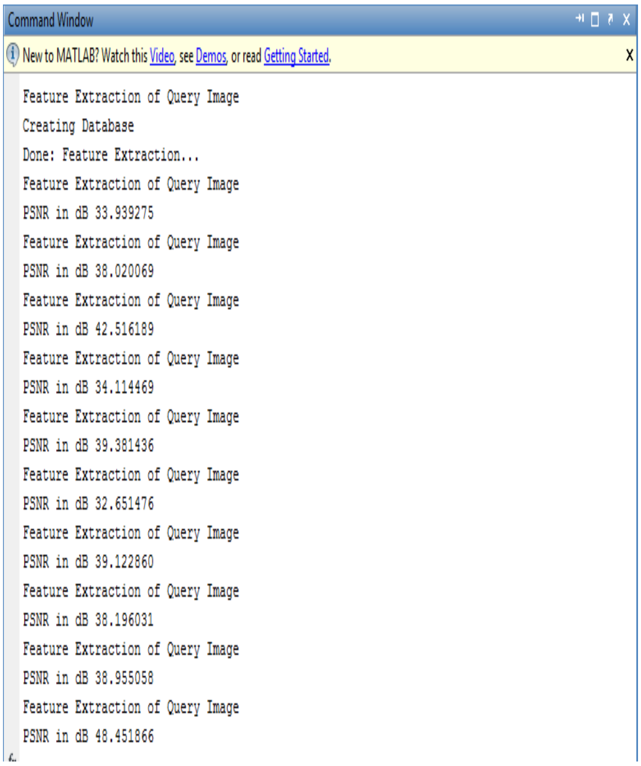


Figure 3. Set of output colour approximated images



```
Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.
Feature Extraction of Query Image
Creating Database
Done: Feature Extraction...
Feature Extraction of Query Image
PSNR in dB 33.939275
Feature Extraction of Query Image
PSNR in dB 38.020069
Feature Extraction of Query Image
PSNR in dB 42.516189
Feature Extraction of Query Image
PSNR in dB 34.114469
Feature Extraction of Query Image
PSNR in dB 39.381436
Feature Extraction of Query Image
PSNR in dB 32.651476
Feature Extraction of Query Image
PSNR in dB 39.122860
Feature Extraction of Query Image
PSNR in dB 38.196031
Feature Extraction of Query Image
PSNR in dB 38.955058
Feature Extraction of Query Image
PSNR in dB 48.451866
```

Figure 4. PSNR values of output images

IV. CONCLUSION

This paper presents a framework for the assessment of perceived image differences. 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) are created based on the framework using IDFs adopted from the terms of the SSIM index. They are numerical representations of assumptions about perceptually important achromatic and chromatic distortions. By observing results it is clear that the accuracy of image difference prediction is more than the existing one. Around 85% of accuracy is achieved in predicting color image of a gray image under test. It is believed that accuracy can be improved more than this.

V. FUTURE WORK

Future research should focus on the creation of an improved image-difference database of gamut-mapped images. The images used in most gamut-mapping experiments exhibit similar distortions, e.g., reduced chroma and almost no change in hue. IDMs trained on such data may underestimate the importance of chroma changes because all images exhibit reduced chroma. For optimal results, a database with highly uncorrelated distortions is required. To test if further improvements are possible using only low-level image-difference features, both semantic and nonsemantic distortions should be included into such a database. In this project around 85% of the accuracy is achieved while predicting the image difference. The maximum PSNR achieved in this project is around 48. It can be improved further if more care is taken on improving reduced chroma.

REFERENCES

1. G. Hong and M. R. Luo. Perceptually based colour difference for complex images. In Proceedings of the 9th Congress of the International Colour Association, pages 618–621, Rochester, NY, 2001.
2. Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. Image quality assessment: From error visibility to structural similarity. IEEE Transactions on Image Processing, 13(4):600–612, 2004.
3. P.-L. Sun and J. Morovic. What differences do observers see in colour image reproduction experiments? InFirst European Conference on Color in Graphics, Imaging, and Vision, pages 181–186,Poitiers, France, 2002.
4. Lissner, J. Preiss, and P. Urban. Predicting image difference based on image-difference features. In19th Color and Imaging Conference, pages 23–28, San Jose, CA, 2011.
5. X. Zhang and B. A. Wandell. A spatial extension of CIELAB for digital color image reproduction. Society for Information Display Symposium Technical Digest, 27:731–734, 1996.
6. Lissner and P. Urban. Toward a unified color space for perception-based image processing. IEEE Transactions on Image Processing, 21(3):1153–1168, 2012.
7. CIE Publication No. 142. Improvement to industrial colour-difference evaluation. Technical report, Central Bureau of the CIE, Vienna, Austria, 2001.
8. Z. Wang, E. P. Simoncelli, and A. C. Bovik. Multi-scale structural similarity for image quality assessment''. In Proceedings of the 37th IEEE Asilomar Conference on Signals, Systems and Computers, pages 1398–1402, Pacific Grove, CA, 2003.
9. P. Zolliker, Z. Bara´ nczuk, and J. Giesen. Image fusion for optimizing gamut mapping. In 19th Color and Imaging Conference, pages 109–114, San Jose, CA, 2011.
10. 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.

11. P. Zolliker, Z. Bara ´nczuk, and J. Giesen, "Image fusion for optimizing gamut mapping," inProc. 19th Color Imag. Conf. , San Jose, CA, 2011,pp. 109–114.
12. N. Damera-Venkata, T. D. Kite, W. S. Geisler, B. L. Evans, and A. C. Bovik, "Image quality assessment based on a degradation,"IEEE Trans. Image Process. , vol. 9, no. 4, pp. 636–650, Apr.2000.
13. Z. Wang and A. C. Bovik, "A universal image quality index," IEEE Signal Process. Lett., vol. 9, no. 3, pp. 81–84, Mar. 2002.
14. H. R. Sheikh, A. C. Bovik, and G. de Veciana, "An information fidelity criterion for image quality assessment using natural scene statistics," IEEE Trans. Image Process., vol. 14, no. 12, pp. 2117–2128, Dec. 2005.
15. H. R. Sheikh and A. C. Bovik, "Image information and visual quality," IEEE Trans. Image Process. , vol. 15, no. 2, pp. 430–444, Feb.2006.
16. D. M. Chandler and S. S. Hemami, "VSNR: A wavelet-based visual signal-to-noise ratio for natural images," IEEE Trans. Image Process. , vol. 16, no. 9, pp. 2284–2298, Sep. 2007.
17. J. Hardeberg, E. Bando, and M. Pedersen, "Evaluating colour image difference metrics for gamut-mapped images," Colorat. Technol. , vol. 124,
no. 4, pp. 243–253, 2008.
18. Ingmar Lissner, Jens Preiss, Philipp Urban, Matthias Scheller Lichtenauer, and Peter Zolliker ''Image-Difference Prediction:From Grayscale to Color '' IEEE Trans. Image Process, vol. 22, no. 2, Feb 2013.