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Quantification of Color Artifacts for the Evaluation of Color Filter Array Demosaicking

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***Abstract*—Most Image Quality Assessment (IQA) methods measure the overall image quality including all visible and non-visible errors. They often do not correlate well with visual assessment particularly when non-visible errors are large in proportion. In particular, color artifacts are a crucial factor in visual assessment, but they might only have a small contribution to the total errors as they are often minorities. Hence, it is desirable to specifically measure color artifacts alone, excluding other errors. One application for such measurement is that color artifacts are the main visible errors produced by Color Filter Array (CFA) demosaicking algorithms. By formalizing the perception that color artifacts manifest as distinct visual color variation from their original and surrounding colors, a novel IQA method, namely Normalized Color Variation (NCV), is proposed specifically for locating and quantifying color artifacts. It gives a NCV index which is a measure of the degree of color artifacts. It has been shown that our proposed NCV method based on the formalization of the perception of color artifacts correlated well with our visual perception. Its NCV index has proven to be a good indicator of the degree of color artifacts and is virtually independent of other errors.**

***Index Terms*—color artifacts, Normalized Color Variation (NCV), image quality assessment, hue assumption, CFA demosaicking**

I. Introduction

Most Image Quality Assessment (IQA) methods are based on the overall errors between a processed image and its original. Common image quality assessment methods including Color Peak Signal - to - Noise Ratio (CPSNR) [1], and Gradient Magnitude Similarity Deviation (GMSD) [2] will measure the overall errors in a processed image, but are incapable of distinguishing different types of errors such as interpolation errors, color artifacts, blurring, and motion artifacts. In this paper, we proposed a novel Normalized Color Variation (NCV) method with a NCV index for image quality assessment to identify and measure errors due to color artifacts specifically.

Color artifacts, including false color [3]-[7], zipper effect [6]-[9] and color bleeding [10]-[13], are errors produced by various color image processing techniques such as Color Filter Array (CFA) demosaicking [6]-[8], [14]-[30] and image compression [31], but not caused by blurring in general for example. In this paper, our proposed method can detect and quantify color artifacts while remaining unaffected by other errors. While there has not been any formal definition of color artifacts [3]-[31], the general perception of color artifacts are pixels with distinct visual color variation from their original and neighboring color values. To conceptualize this idea, when a processed pixel with a color variation between its original is larger than the color variation between the original and its surrounding colors, that processed color is considered as distinct and that pixel is classified as a color artifact. In other words, pixels with errors due to blurring will not be classified as color artifacts as they do not have distinct color variation from their original and neighboring color pixels.

The remainder of the paper is organized as follows. Section 2 introduces our proposed NCV method and its index. Section 3 presents the quantitative and visual assessment results with our conclusion in Section 4.

II. Proposed NCV Method

Since the general perception of a color artifact pixel is determined by its color variation from its original and surrounding colors, we propose to measure this color variation by measuring the change in hue. For CFA demosaicking, the common CFA is the Bayer pattern [32] in the RGB color space. Hence it is desirable to detect color artifacts in the same color space. According to the hue assumption, the difference between the color values of two adjacent pixels is a constant [8], [18], [33]. Any change in that constant value in the corresponding region in the processed image is a reflection of the change in hue in that region. Hence, the change in hue can be quantified by the change of this constant. Therefore, if the processed and original pixels have a similar color, the following is true for the red and green pixels at the same pixel location (i,j) according to the hue assumption [8]:

$$G_{i,j}^{P} - R_{i,j}^{P} \approx G_{i,j}^{O} - R_{i,j}^{O} \tag{1}$$

where G^P, R^P, and G^O, R^O, are the green and red pixels in the processed and original images respectively. As a result, the following equation is implied:

$$\left|G_{i,j}^{P} - G_{i,j}^{O}\right| \approx \left|R_{i,j}^{P} - R_{i,j}^{O}\right| \tag{2}$$

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Let $\alpha_{i,j}$ be the absolute difference of a color value between the processed and the original pixels in (2), therefore

$$\alpha^{G}_{i,j} \approx \alpha^{R}_{i,j} \qquad (3)$$

Similarly, for the blue pixels, we define:

$$\alpha^{B}_{i,j} = \left| B^{P}_{i,j} - B^{O}_{i,j} \right| \qquad (4)$$

For the same reason,

$$\alpha^{G}_{i,j} \approx \alpha^{R}_{i,j} \approx \alpha^{B}_{i,j} \qquad (5)$$

Based on the hue assumption, a constant hue implies that $\alpha^{G}_{i,j}$, $\alpha^{R}_{i,j}$, $\alpha^{B}_{i,j}$ are approximately equal. Hence any fluctuations among those values implies a change in hue. Their standard deviation is a measure of the degree of fluctuation, and therefore it is a good indicator of the degree of change in hue. As a result, we define the color variation, $\sigma^{\alpha}_{i,j}$, as the standard deviation among these three color differences as follows:

$$\sigma^{\alpha}_{i,j} = \sqrt{\frac{(\alpha^{R}_{i,j} - \mu^{\alpha}_{i,j})^2 + (\alpha^{G}_{i,j} - \mu^{\alpha}_{i,j})^2 + (\alpha^{B}_{i,j} - \mu^{\alpha}_{i,j})^2}{3}} \qquad (6)$$

where i=1,2…,M, j=1,2,…,N, M and N are the dimensions of the image, and $\mu^{\alpha}_{i,j}$ is the mean given by:

$$\mu^{\alpha}_{i,j} = \frac{1}{3}\left(\alpha^{R}_{i,j} + \alpha^{G}_{i,j} + \alpha^{B}_{i,j}\right) \qquad (7)$$

Since the general perception of a color artifact pixel is a pixel with a distinct color variation between itself and its original, in order to formalize this idea, the amount of color variation to be considered as distinct is quantified by a threshold for the classification of color artifacts. When the color variation is larger than that threshold, the corresponding pixel is classified as a color artifact. The maximum color variation within a region in the original image is used as a reference for the allowable color variation between a processed pixel and its original in that region. The threshold for classification of color artifacts is a relative quantity based on this maximum color variation within that region.

To determine the threshold value for the classification of color artifacts for the pixel at (i,j), let S be the shell which is a set of color pixels surrounding it in the original image [34], [35]. We define S^R, S^G, S^B be a shell for the red, green, and blue color planes respectively as follows:

$$S^R = \left\{ \begin{matrix} R^O_{i-1,j-1} & R^O_{i-1,j} & R^O_{i-1,j+1} \\ R^O_{i,j-1} & & R^O_{i,j+1} \\ R^O_{i+1,j-1} & R^O_{i+1,j} & R^O_{i+1,j+1} \end{matrix} \right\} \qquad (8)$$

$$S^G = \left\{ \begin{matrix} G^O_{i-1,j-1} & G^O_{i-1,j} & G^O_{i-1,j+1} \\ G^O_{i,j-1} & & G^O_{i,j+1} \\ G^O_{i+1,j-1} & G^O_{i+1,j} & G^O_{i+1,j+1} \end{matrix} \right\} \qquad (9)$$

$$S^B = \left\{ \begin{matrix} B^O_{i-1,j-1} & B^O_{i-1,j} & B^O_{i-1,j+1} \\ B^O_{i,j-1} & & B^O_{i,j+1} \\ B^O_{i+1,j-1} & B^O_{i+1,j} & B^O_{i+1,j+1} \end{matrix} \right\} \qquad (10)$$

For each of the three shells of the original image, eight absolute differences, $\beta_{m,n}$, are determined between the pixel at (i,j) and each of the eight pixels in the shell as follows:

$$\beta^{R}_{m,n} = \left| R^{O}_{i,j} - S^{R}_{m,n} \right|$$

$$\beta^{G}_{m,n} = \left| G^{O}_{i,j} - S^{G}_{m,n} \right| \qquad (11)$$

$$\beta^{B}_{m,n} = \left| B^{O}_{i,j} - S^{B}_{m,n} \right|$$

where (m,n) ∈ {(i−1,j−1), (i−1,j), (i−1,j+1), (i,j−1), (i,j+1), (i+1,j−1), (i+1,j), (i+1,j+1)}.

Similar to (6), the color variation, $\sigma^{\beta}_{m,n}$, in the original image is given as follows:

$$\sigma^{\beta}_{m,n} = \sqrt{\frac{(\beta^{R}_{m,n} - \mu^{\beta}_{m,n})^2 + (\beta^{G}_{m,n} - \mu^{\beta}_{m,n})^2 + (\beta^{B}_{m,n} - \mu^{\beta}_{m,n})^2}{3}} \qquad (12)$$

where $\mu^{\beta}_{m,n}$ is the mean value of the three color absolute differences given by the following:

$$\mu^{\beta}_{m,n} = \frac{1}{3}\left(\beta^{R}_{m,n} + \beta^{G}_{m,n} + \beta^{B}_{m,n}\right) \qquad (13)$$

The threshold value (T) is therefore defined as the maximum of these eight color variations plus a determined tolerance (δ) as follows:

$$T = \max\{\sigma^{\beta}_{m,n}\} + \delta \qquad (14)$$

where (m,n) ∈ {(i−1,j−1), (i−1,j), (i−1,j+1), (i,j−1), (i,j+1), (i+1,j−1), (i+1,j), (i+1,j+1)}.

For 24-bit RGB color images, each color is quantized to 8-bit or 256 levels. As the intensity range is normalized to [0, 1], each quantization step size, q, is equal to 1/256. For any color variation to be visible, the absolute color differences for each color plane must be at least equal to one quantization step. To accommodate for the maximum possible quantization errors of the difference between two quantized intensity values, the tolerance to guarantee these two discrete values are distinct is therefore equal to two quantization steps as follows:

$$\delta = 2q \approx 7.81 \times 10^{-3} \qquad (15)$$

Let L be a set which contains the locations of color artifact pixels in the processed image,

$$L = \{(i, j) : \sigma^{\alpha}_{i,j} > T\} \qquad (16)$$

and $|L|$ be the cardinal number of the set L. The percentage, p, of the total area which contains color artifact pixels in the processed image is given by:

$$p = \frac{|L|}{M \times N} \times 100\% \tag{17}$$

where M and N are the dimensions of the image. This percentage, p, can serve as a supplementary index to quantify the size of total affected areas by color artifacts.

The proposed Normalized Color Variation (NCV) index is defined by the following:

$$NCV = \frac{\sum_{i,j \in L} \sigma_{i,j}^{\alpha}}{M \times N} \tag{18}$$

where M and N are the dimensions of the image.

The NCV index is the total color variation of all color artifact pixels identified in the whole processed image and normalized by the image size. It is therefore a measure of the degree of color artifacts produced in that image. The NCV index is an effective and suitable tool for image quality assessment for the comparison of color artifacts produced by various algorithms, whereby an algorithm producing less color artifacts will give a lower NCV value, and a zero NCV value implies no color artifacts detected. Fig. 1 gives the flowchart of our proposed NCV method.

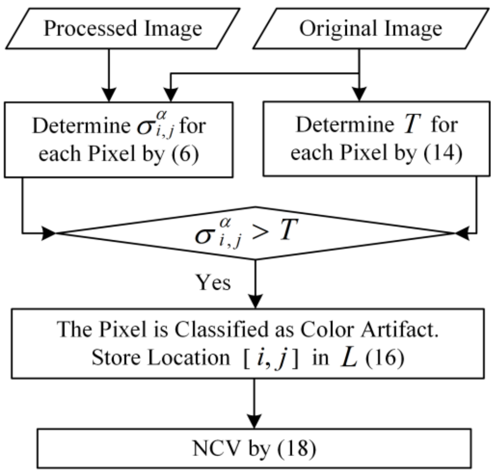

Figure 1. Flowchart of the proposed NCV method.

III. RESULTS

Various types of errors, including color artifacts, blurring and compression, were used to evaluate the performance of our proposed NCV method quantitatively and visually and to illustrate its independence of errors other than color artifacts. For generating CFA demosaicking errors, five algorithms, namely EIG [36], WM-HOI [18], RI [26], MDWI [19] and Bilinear, producing various degrees of color artifacts were used. For generating other errors, Gaussian and motion blur, and JPEG2000 [37]-[40] were used. Gaussian blur was simulated using a 5×5 filter window with a standard deviation of unity, and motion blur, which approximates the linear motion of a camera, was simulated using the same window size.

TABLE I. IMAGE QUALITY ASSESSMENT: CPSNR [1], GMSD [2], ZE [8] AND PROPOSED NCV FOR KODAK DATASET

	CPSNR (dB)	GMSD ($\times10^{-2}$)	ZE (%)	NCV ($\times10^{-3}$)
Blurring				
Gaussian	29.52	4.413	6.45	$< 10^{-7}$
Motion	28.89	5.814	10.07	$< 10^{-7}$
Demosaicking				
EIG [36]	40.37	1.249	3.68	0.281
WM-HOI [18]	39.35	1.578	7.12	0.845
RI [26]	38.99	1.378	7.81	0.981
MDWI [19]	37.04	1.680	12.06	1.606
Bilinear	30.25	4.483	40.18	10.362
JPEG2000 with different compression ratios				
100%	50.43	0.077	0.04	0
25%	49.85	0.090	0.09	0
10%	42.16	0.712	3.50	$< 10^{-7}$
1%	29.20	8.692	13.88	2.359

TABLE II. IMAGE QUALITY ASSESSMENT: CPSNR [1], GMSD [2], ZE [8] AND PROPOSED NCV FOR IMAX DATASET

	CPSNR (dB)	GMSD ($\times10^{-2}$)	ZE (%)	NCV($\times10^{-3}$)
Blurring				
Gaussian	31.08	3.498	12.68	$< 10^{-7}$
Motion	29.44	5.628	16.37	$< 10^{-7}$
Demosaicking				
RI [26]	36.82	1.472	12.00	0.251
MDWI [19]	36.13	2.061	11.74	0.373
WM-HOI [18]	35.04	2.500	12.42	0.344
EIG [36]	34.40	3.753	12.01	0.740
Bilinear	32.34	2.694	28.52	2.804
JPEG2000 with different compression ratios				
100%	49.95	0.078	0.15	0
25%	45.98	0.196	3.24	0
10%	39.18	1.100	12.84	$< 10^{-7}$
1%	28.29	10.215	21.79	2.458

To quantitatively evaluate the sensitivity of various IQA tools and our proposed NCV method to the degree of color artifacts, Color Peak Signal-to-Noise Ratio (CPSNR) [1], Gradient Magnitude Similarity Deviation (GMSD) [2] and Zipper Effect (ZE) [8] were used with all the 24 images from the Kodak dataset [41] and all the 18 images from the IMAX dataset [17]. CPSNR measures the total errors in the processed image, GMSD measures image distortion and can predict accurately perceptual image quality in the processed image, and ZE is a measure of one form of color artifacts consisting of on–off patterns created in saturated color regions. Tables I and II show the average numerical results for the different processing techniques using all the 42 test images from the Kodak and IMAX datasets respectively. From Tables I and II, our proposed NCV index gives negligible values when minimal color artifacts were produced by the blurring methods, because blurring does not generally produce color artifacts, while the other IQA methods still produce considerable values including ZE which is intended to detect only one form of color artifacts. Hence, those IQA methods do not give a true reflection of the actual degree of color artifacts. Moreover, for JPEG2000 with a compression ratio of 100% for instance, the decompressed image is visually indistinguishable from the original image with no color artifacts, but those IQA methods still produced some values reflecting the presence of errors, while our NCV index values are negligible showing no color artifacts detected. From Tables I and II, it has been shown that our proposed NCV method is able to produce a better correlated index in quantifying color artifacts than the other IQA methods. Our proposed NCV index will also find applications to assess color accuracy in color image processing.

To examine the effectiveness of our proposed method in locating color artifacts for visual assessment, one image from each of the Kodak [41] and IMAX [17] datasets as shown in Fig. 2(a) and (b) respectively were used. The 2nd and 4th rows of Fig. 2(c)-(g) give the outputs of various demosaicking algorithms [36], [18], [26], [19] and those of Fig. 2(h)-(i) give the Gaussian and motion blurred images respectively. To generate compression errors, Fig. 2(a) and (b) were compressed by JPEG2000 with a compression ratio of 1% [40]. Their decompressed images are shown in 2nd and 4th rows of Fig. 2(j).

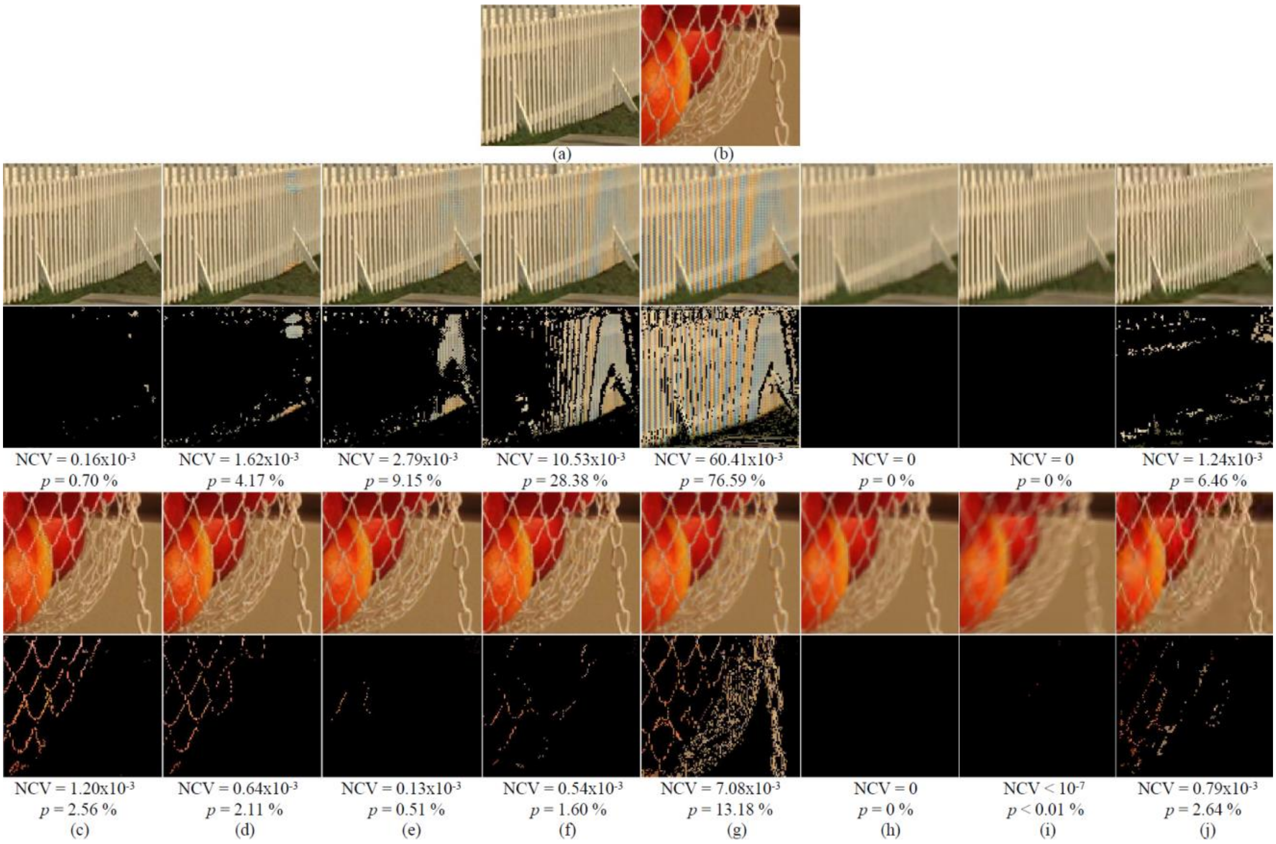

Figure 2. Cropped regions of the original image from (a) Kodak dataset and (b) IMAX dataset, and the processed images (c) to (j) using EIG [36], WM-HOI [18], RI [26], MDWI [19], Bilinear, Gaussian blur filter, motion blur filter and JPEG2000 [37] respectively.

The color artifact pixels identified in the corresponding 2nd and 4th row images by our method are shown in the 3rd and 5th rows of Fig. 2. The white picket fence region with vertical edges in the 2nd row and the white string net with diagonal and curved edges in the 4th row are well known to cause color artifacts by demosaicking algorithms. The color artifacts, from (c) to (g), which manifest as false color pixels are quite distinguishable from the white picket fence and the white string net, and visually correlate well with the identified color artifacts in the 3rd and 5th rows. For the images in the (h) to (i) columns, it is visually clear that minimal color artifacts were produced by the blurring algorithms and our NCV indices gave negligible values accordingly, even though another error due to blurring in the processed images was substantial. For the images in the (j) column, some degree of color bleeding artifacts were produced by JPEG2000, and these are reflected in the NCV indices as shown. By comparing the images in the 2nd and 4th rows to the corresponding color artifacts identified in the 3rd and 5th rows, it is evident that our proposed method can locate and identify color artifacts specifically. The NCV indices and p values shown correlate well with the degree of color artifacts in the processed images. In general, the NCV index and p both increase with the degree of color artifacts. However, there are cases when the NCV index increases as the p value decreases and vice versa as shown in the Kodak image of Fig. 2(d) and Fig. 2(j). In Fig. 2(d), the NCV index is larger than that of Fig. 2(j) while the p value is smaller. The reason is that even though the total affected area by color artifacts in Fig. 2(d) is smaller, its total color variation is larger, and hence the color artifacts in Fig. 2(d) are more noticeable.

Even though there is no formal definition of color artifacts in the literature with no ground truth for comparison, our experimental results have confirmed that our formalization of the definition of color artifacts based on the maximum color variation in the original image correlates very well with the perception of color artifacts. Hence, our proposed NCV method is suitable for the evaluation of the degree of color artifacts which are the main visible errors produced by CFA demosaicking algorithms.

IV. Conclusion

By formalizing the general perception of color artifacts, a novel Normalized Color Variation (NCV) index has been proposed for image quality assessment to quantify color artifacts for CFA demosaicking. It is based on the measurement of color variation corresponding to the change in hue derived from the hue assumption in the same RGB color space as the CFA Bayer pattern. Using a threshold determined from the original color variation in the original image to distinguish color artifacts from original colors, color artifact pixels can now be effectively identified and located. It has been shown by experimental results that our proposed NCV IQA method can effectively quantify the degree of color artifacts with virtually no influence by other errors. It has been proven to be a very effective IQA method for comparing different CFA demosaicking algorithms in producing various degrees of color artifacts.

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