Camera Image Quality Assessment Without Reference Information

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***Abstract*—Blur plays an key part in evaluating of camera image quality. It leads to decrease of high frequency information and accordingly changes the image energy. Recent researches in quaternion singular value decomposition show that the quaternion's singular values and associated vectors can capture the distortion of color images, and thus singular values can be utilized to assess the sharpness of camera image. Based on this, a novel blind quality assessment method considering the integral color information and singular values of the blurred camera image is proposed for evaluating the sharpness of camera image.Pure quaternion is utilized to represent pixels of the blurred camera image and the energy of every block are obtained. Results confirm the superiority of the proposed blind algorithm in assessing camera images.**[1]

(a)

(b)

(c)

(d)

Fig. 1. Sample realistic blur images from RBID database [20]. (a) Complex motion blur. (b) Uncomplicated motion blur. (c) Out of focus. (d) Other complicated distortions.

I. Introduction

With the wide use of multimedia technology and Internet business, visual information has played key role in human daily lives. But images are oftentimes degraded by different kinds and levels of distortions in compression [1], [2], enhancement [3], [4] and more. So it is urgent to develop effective and efficiency image quality evaluation algorithm to evaluate camera image quality so that it can be utilized for supervisory control and possibly enhancing camera quality.

Scientists have proposed many image assessment metrics so far, which can be basically classified into objective and subjective and quality evaluation methods [5], [6], [7], [8], [9]. According to the image distortion prior knowledge, NR IQA algorithms are also separated into general-purpose and distortion-specific metrics. The latter class includes several typical methods towards blurriness/sharpness [10], [11], [12], [13], blockiness [14], [15], contrast adjustment [16], multiply distortions [17], etc.

Although current image blur metrics are good at simulated blur distortion, they poorly perform for realistic camera image assessment, which can be found from experimental results in Section 4. Realistic camera images contain complicated blur types and suffer from different distortion sources. Sample realistic camera images chosen from the RBID database [20] are presented in Fig. 1. It was observed that the realistic camera blur distorted images contain many categories of blur distortions. Image (a) may be classified into the simple motion class that could by fairly considered linear caused by camera movements. Image (b) consists of complex motion blur which caused by complex motion paths. Image (c) belongs to out of focus category which caused by the whole image is out of focus. Image (d) contains complex blur distortion which may contains any other types of degradation. Hence, it is challenging to assess realistic blur images quality .

This paper concentrates on blind camera image sharpness assessment. As far as we know, our research is the pioneer study to propose a blind sharpness of camera images on the basis of quaternion singular values decomposition which concerns the inevitable effect of color information on the sharpness assessment. The layout of this paper is arranged below. The theories of some relevant models employed in this paper is presented in the second section. The description of our designed model is illustrated in the third section. The superiority of the BQSVD model with lately devised blind sharpness techniques are verified on the RBID database [20] in the fourth section. We derive some conclusions in the fifth section.

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(a) (b) (c) (d) (e) (f)

Fig. 2. Influence of changing singular values σ. The original image is shown in (a). The number of σ_{i} set as (b) i = 512. (c) i = 200. (d) i = 100. (e) i = 30. (f) i = 10.

(a) (b) (c) (d) (e) (f)

Fig. 3. Influence of changing $\mathbf{U}\mathbf{V}^T$ values. (a) denotes pristine image. The number of group $\mathbf{U}_i\mathbf{V}_i^T$ set as (b) i = 512. (c) i = 300. (d) i = 100. (e) i = 50. (f) i = 10.

II. Background

Singular value decomposition (SVD) is one of the most famous transformation in linear algebra. Formally, the mathematical definition of SVD for an image matrix $\mathbf{W}_{m\times n}$ can be defined as

$$\mathbf{W}_{m\times n} = \mathbf{U}_{m\times m}\mathbf{S}_{m\times n}\mathbf{V}_{m\times n} \tag{1}$$

where $\mathbf{S}$ is a rectangular diagonal matrix. $\mathbf{V}$ and $\mathbf{U}$ are unitary matrix. σ_i corresponds to diagonal entries, which are also the W's singular values. We listed them in a decreasing rank. The V's and U's columns are orthogonal bases. The matrix $\mathbf{U}\mathbf{v}^T$ can represent the image structure (the basis image) [21]. To visually view the effect of singular value and singular vector on the image, we show examples in Fig. 2 and Fig. 3.

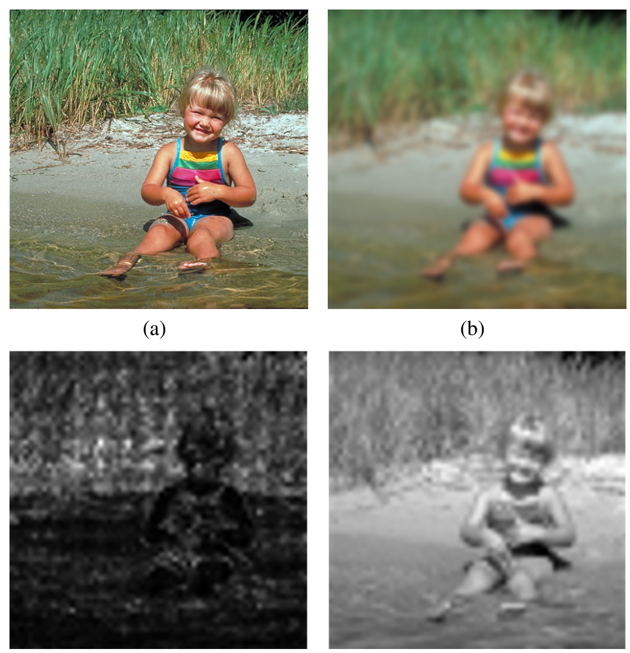
Singular values or singular vectors can describe features of images, which may be used for quality assessment. In 1843, the concept of quaternion [22] is proposed by Hamilton. Generally speaking, a quaternion encompasses four parts, three imaginary numbers and one real number. We can understand quaternion to be an expansion of complex, namely hyper complex numbers.

The case with a null real part (the first real number $a = 0$) refers to a pure quaternion, which can be employed to characterize color image. To specify, we can express a color image based on the pure quaternion:

$$\mathbf{Q}_I = F_R i + F_G j + F_B k \tag{2}$$

where $\mathbf{R}$, $\mathbf{G}$ and $\mathbf{B}$ correspond to an color image's red, green and blue channels.

SVD is a factorization of a matrix. Hence, it can be directly applied to gray images. For a color image, one way is to directly operate SVD on one channel of the color image, and another way is through transforming the color image to extract the brightness level information before using the SVD method to deal with. Both of the two ways cannot handle the color image as a whole, neglecting the color information of the camera image. However, the quaternion model can describe the color image information as a whole, according to the definition of SVD on the complex adjoint matrix, singular



(a) (b)

(c) (d)

Fig. 4. The top two images (a)-(b) are the pristine childswimming image and its associated blurred one. The bottom two images (c)-(d) are the distortion maps of the gray scale SVD and QSVD of the blur distorted images, respectively.

value decomposition of quaternion (QSVD) is utilized to evaluate color images quality. We define the QSVD according to [23], [24]:

$$\mathbf{F}_{Q(m,n)} = \mathbf{U}_{m\times m}\mathbf{S}_{m\times n}\begin{pmatrix} \sum_r & 0 \\ 0 & 0 \end{pmatrix}\mathbf{V}^{\star}_{n\times n} \quad (3)$$

$$\sum_r = diag(\sigma_1, \sigma_2, \cdots, \sigma_r) \quad (4)$$

where $\sum_r$ is real diagonal matrix. These non-negative real numbers are the quaternion matrix $Q(m,n)$'s singular values and r is the rank of $Q(m,n)$. V and U are the right and left $Q(m,n)$'s singular vectors and elements of these two unitary matrixes are all quaternions. $*$ denotes the conjugate transpose.

To intuitional understanding the gray scale SVD that only concentrated on luminance information, and QSVD combined luminance and chrominance information into the IQA model, we give an example in Fig. 4. The subsequent formula is used to construct the distortion map [25].

$$\mathbf{D}(i) = \sqrt{\sum_{i=1}^{P}(\mathbf{S}_{dis}(i) - \mathbf{S}_{org}(i))^2} \quad (5)$$

where $\mathbf{S}_{org}$ and $\mathbf{S}_{dis}$ denotes the singular values which are obtained by gray scale SVD and QSVD method of the corrupted block, P is the size of block. A gray scale image can be obtained representing distortion map which consisted by mapping $\mathbf{D}(i)$ values to the range [0, 255].

It is well known that the gray scale SVD method, which only extracts the luminance components and discards many effective components, can not intuitionally reflect the distortion degree. However, QSVD performs better, which implies that the chrominance information should be considered when assess color image quality.

III. Proposed Blind Quality Metric

So far, many visual quality models have been addressed for objective image quality assessment. They are good in simulated distortions, but poorly perform for realistic camera image assessment. In this research we deploy QSVD to measure the sharpness of camera images. The theoretical foundation is that Frobenius norm of hyper complex matric can be used to represent the energy of color camera images, and we have a reason to believe energy change can be effectively reflect the extent of blur.

In our work, a novel hyper complex SVD-based blind camera image assessment metric is proposed. The proposed algorithm includes three main stages. First, the input blurred visual signal is transferred into the color space of LAB, and is represented by pure quaternion. Second, two components are calculated: 1) quaternion singular values for blocks; 2) energies of the blurred camera image blocks . Finally, SVR-based learning is utilized to acquire the blur score of an input camera image.

According to the previous researches, it was found that the HVS has higher sensitivity to luminance variations than chrominance [25]. Therefore, most previous IQA methods were devised based on the mathematical modeling. Our metric considers the inevitable influence of color information on the sharpness assessment. So, in the proposed metric, the blurred camera image is first converted into widely used LAB color space [26].

(a) $\mathbf{E} = 46.4592$ (b) $\mathbf{E} = 46.8640$ (c) $\mathbf{E} = 53.3717$

Fig. 5. Three realistic camera images and their average energies.

Considering the fact that the LAB color space is a well approximation of human vision, unlike the CMYK and RGB color space, it includes all the colors information to the human eye. After the transformation, the pure quaternion is used to express every pixels of the transformed blurred camera image:

$$\mathbf{F}_Q = F_L i + F_A j + F_B k \quad (6)$$

where L denotes the luminance information; A and B for the color dimensions. Frobenius norm can be utilized to represent the energy $\mathbf{E}$ of a matrix $\mathbf{A}$:

$$\mathbf{E} = \|\mathbf{A}\|_F. \quad (7)$$

Therefore, Frobenius norm of hyper complex matric $\mathbf{A}$ can be used to represent the energy of color camera images ($\mathbf{E}$). According to the definition of the hyper complex singular value decomposition, for any hyper complex matrix $\mathbf{A} \in \mathbf{H}^{M\times N}$, there exist two unitary hyper complex matrix $\mathbf{V}$ and $\mathbf{U}$, which satisfy the subsequent relationship:

$$\mathbf{A} = \mathbf{U}\begin{pmatrix} \sum_r & 0 \\ 0 & 0 \end{pmatrix}\mathbf{V}^{\star} \quad (8)$$

where $\mathbf{U} \in \mathbf{H}^{M\times M}$,$\mathbf{V} \in \mathbf{H}^{N\times N}$. Superscript $\star$ denotes conjugate transpose, $\sum_r$ is a matrix that contains the number of r non-empty values. According to Eq. (7) and Eq. (8), the energy of color camera image can be defined as the Frobenius norm of hyper complex matrix singular values. In other words, the singular values of hyper complex matrix denotes the energy feature of the color image, and it can be utilized as benchmark for assessing the quality of color image. It serves as the theoretical basis for our proposed blind camera sharpness assessment metric.

Blur changes the image information existed in high frequency, and the quaternion singular values accordingly vary. To give a straightforward view of the relation of quaternion singular values and blur, an example is shown in Fig. 5, in which three realistic camera images with different blur scales and their energy are shown. It is can be viewed from the figure that the energy change with the degree of blur. Therefore, the energy can be utilized to test the sharpness degree of camera images with the same content.

TABLE I
PERFORMANCE COMPARISON ON THE RBID DATABASE.

Metric	PLCC	SRCC	KRCC	RMSE
CPBD [10]	0.2704	0.2711	0.1820	1.2053
S3 [11]	0.4270	0.4253	0.2921	1.1320
ARISM [12]	0.1841	0.1841	0.1258	1.2305
BIBLE [13]	0.3816	0.3846	0.2611	1.1572
NIQE [18]	0.4608	0.4584	0.3089	1.1111
NFERM [19]	0.4738	0.4679	0.3183	1.1025
BQSVD (Proposed)	**0.4849**	**0.4752**	**0.3230**	**1.0949**

According to Gu *et al.* [27], image size and observing distance have great effect on the perceived image quality. Motivated by this, we adopt down-sampling way to acquire the energy of four scale images as features. And the $t\%$ highest variance blocks are used as features to train the SVR model [28]. Afterwards, the well-established regression module is applied for inferring an image's sharpness score.

We summary the proposed BQSVD algorithm below. The input blurred RGB camera image $I(x, y, z)$ is first converted to LAB color space. Next, we separate the image into blocks of equal-size non-overlap $P \times P$. The block size adopted in the proposed method is 8×8, since the standard block size used in many image processing applications are all 8×8 based. In [11], the sharpness score was obtained by taking the 1% highest values in the obtained map. In our proposed method, the blocks are ordered by their variances, and the $t\%$ highest energy blocks are deployed to derive the quality estimation.

IV. VALIDATIONS

The performance of our quality model is verified using the realistic blur database (RBID) camera image quality database [20]. The images in this database are obtained for various scenes, camera apertures. The database includes 586 images with resolutions ranging from 640×480 to 2816×2112 pixels which contains not only simple cases, but also complicated and realistic ones. Mean opinion score is used to measured the subjective image quality scores in the RBID database, which with values from 0 to 5.

According to the VQEG's suggestions [29], four criteria indexes are introduced for testing the performance, including KRCC, SRCC, RMSE, and PLCC. The first two indexes are towards measuring the monotonicity in predictions, whereas the other two are towards evaluating the accuracy in predictions. The performance of our developed IQA model is computed on the RBID database and compared with recently proposed blind sharpness/quality methods, including CPBD [10], S3 [11], ARISM [12], BIBLE [13], NIQE [18], as well as NFERM [19]. We tabulate experimental results in Table II, in which we mark the highest results in boldfont. We notice that our designed metric produces the optimal results, which achieves the largest KRCC, SRCC and PLCC, as well as the lowest RMSE compared with prevailing competitors.

V. CONCLUSION

We in this paper have came up with a referenceless quality model for realistic camera image sharpness based upon quaternion singular value decomposition. A comparison of our Q-SVD with popular blind sharpness measures is conducted using the RBID database. Results of trails demonstrate the superiority of our designed blind IQA metric on the RBID database. Apart form the superior performance, to our knowledge, our BQSVD technique is the first one using hypercomplex singular value decomposition towards blind IQA problem.

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