No-Reference Quality Assessment of Enhanced Images

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Abstract: Image enhancement is a popular technique, which is widely used to improve the visual quality of images. While image enhancement has been extensively investigated, the relevant quality assessment of enhanced images remains an open problem, which may hinder further development of enhancement techniques. In this paper, a no-reference quality metric for digitally enhanced images is proposed. Three kinds of features are extracted for characterizing the quality of enhanced images, including non-structural information, sharpness and naturalness. Specifically, a total of 42 perceptual features are extracted and used to train a support vector regression (SVR) model. Finally, the trained SVR model is used for predicting the quality of enhanced images. The performance of the proposed method is evaluated on several enhancement-related databases, including a new enhanced image database built by the authors. The experimental results demonstrate the efficiency and advantage of the proposed metric.

Keywords: image enhancement; quality assessment; no-reference; perceptual feature; SVR

I. INTRODUCTION

Nowadays, image quality assessment (IQA) has been drawing increasing attention. Quality assessment is highly demanded in modern image processing and recognition problems [1], such as image/video coding, restoration, retargeting, forensics and social videos [2-13]. In the past few years, extensive work has been done to the quality assessment of degraded images, mostly based on structural distortion measurement [14]. However, these metrics are very likely to be problematic in real-world scenarios [15]. Therefore, quality models for specific application domains have been an emerging direction in the quality evaluation community.

Image enhancement has been widely adopted to improve the visual quality of images [16]. With the increasing prevalence of mobile devices, which have been equipped with compact cameras, image enhancement functionality has been embedded into image processing softwares for providing better Quality of Experience (QoE). In the current image enhancement researches, the quality of enhanced images is mainly judged by subjective test, which is laborious and expensive. Objective quality models are useful for benchmarking and optimization of image enhancement algorithms. The current image quality models are mainly designed for degraded images, so they are very limited in predicting the quality of enhanced images. Quality evaluation of enhanced images is still an open problem.

So far, very little work has been dedicated to the quality evaluation of enhanced images. Vu *et al.* [17] proposed a full-reference (FR) quality metric for digitally retouched images by improving traditional quality models with an enhancement module. Specifically, contrast, sharpness and saturation changes between the original and retouched images were combined to produce the enhancement measurement. Li *et al.* [18] proposed a FR quality metric for retouched images by measuring structure and color changes. Structure change was measured by the gradient similarity between the original and retouched images. For color, colorfulness and saturation were considered. These two metrics have shown promising performances on a digitally retouched image database, which consists of enhanced images obtained using Photoshop. However in practice, the similarity/distance between the retouched and original images does not necessarily indicate the actual quality, because over-enhancement may occur in real-world scenarios. In [19], Fang *et al.* addressed a no-reference (NR) quality metric for contrast changed images based on Natural Scene Statistics (NSS). A large number of natural images were first used to train a NSS model. The quality of a test image was defined as the deviation of its NSS features from the pre-trained NSS model. Wang *et al.* [20] proposed a patch-based contrast quality index. Image local patches were decomposed into three components, including mean intensity, signal strength and signal structure. Then they were evaluated in different ways, followed by a pooling to produce the overall quality score. The quality metrics in [19] and [20] are specifically designed for image contrast change, which is one of the many factors in image enhancement. Therefore, they cannot be used to predict the quality of the general enhanced images. The aforementioned quality metrics are limited in application scenarios, so more general quality models for image enhancement are still lacking.

In this paper, a new quality model for the general image enhancement is proposed. With the consideration that image quality is usually determined by different factors, we achieve the goal by investigating three perceptual aspects of enhanced images, including non-structural information, sharpness and naturalness. A set of 42 features are extracted and used to train a support vector regression (SVR) model. The quality of a query image is predicted based on SVR regression. An enhancement image database (EID) is built to evaluate the performance of the proposed method. Experimental results on EID and three related databases demonstrate the effectiveness and advantages of the proposed method.

This paper proposed a no-reference quality metric for digitally enhanced images. Three kinds of features are extracted for characterizing the quality of enhanced images, including non-structural information, sharpness and naturalness.

II. Enhanced Image Database (EID)

Currently, there is only one dataset that can be used for image enhancement quality assessment, i.e., Digitally Retouched Image Quality (DRIQ) [17, 21]. However in DRIQ, the images are obtained by Photoshop, which are not representative of images generated by the general image enhancement algorithms. Therefore, a more diverse database that contains images enhanced by different algorithms and image processing softwares is needed.

2.1 Settings

Forty color images are used to build the database, which are selected to cover diverse contents, including buildings, plants, animals, people, etc. These images are typically characterized by low light, low contrast, underwater, foggy, etc. Fig. 1 shows ten of the images. In order to generate the enhanced images, eight approaches are adopted, including five representative image enhancement algorithms [22-26] and three popular image processing softwares Photoshop, Digital Photo Professional (DPP) and ACDSee [27-29]. To be specific, each image is processed using the eight approaches, producing eight enhanced versions of the image. Finally, a total of 320 enhanced images are produced, which constitute the EID database. It should be noted that all images in the EID database are represented in color format. Fig. 2 shows some example images in the database.

2.2 Subjective test

In order to obtain the ground truth of image quality, subjective test is performed using the single stimulus (SS) method on an Absolute Category Rating (ACR) scale 1-10, corresponding to the worst-best quality. In the test, 25 inexperienced volunteers are involved, including 12 males and 13 females, all aged between 20 and 38. The subjective test is conducted in a lab environment with normal lighting condition. A LCD monitor with resolution 1920´1080 is used to display the images. In order to facilitate rating, a Matlab-based GUI interface is developed, which is shown in Fig. 3. In order to avoid visual fatigue, all subjects are required to finish the test within one hour.

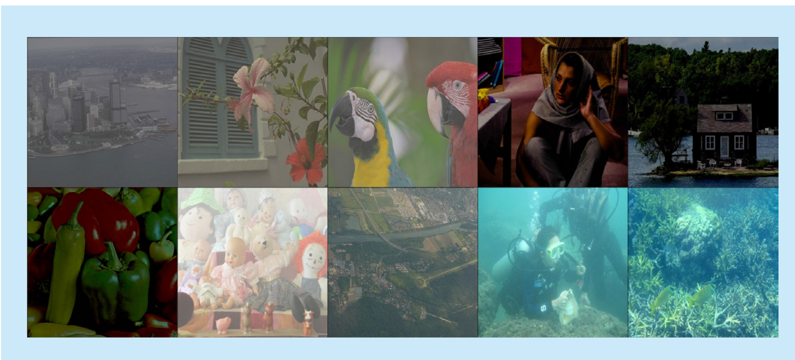

Fig.1 *Ten of the original images used to build the EID database*

Fig.2 *Example enhanced images in the EID database*

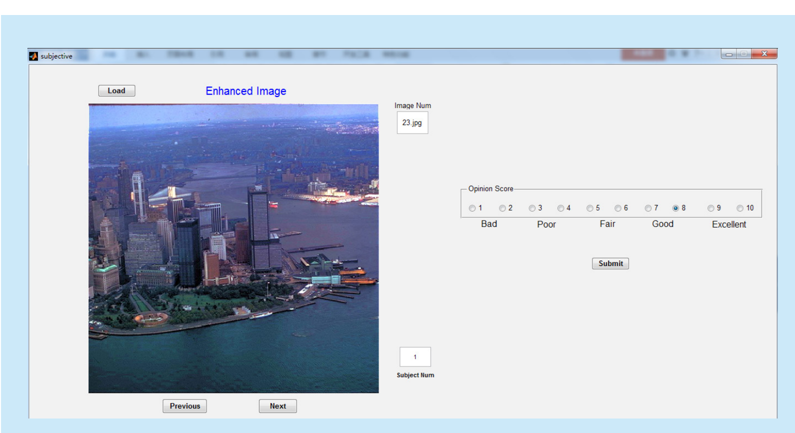

Fig.3 *GUI interface used for quality rating*

After obtaining the rating scores of all subjects, outliers are removed using the method in [30, 31]. For each image, an average of five outliers are removed. Then the mean of the remaining scores are computed and used as the ground truth, which is also known as the Mean Opinion Score (MOS). Fig. 4 shows the final subjective scores of the enhanced image as well as the corresponding standard deviations.

III. Proposed Quality Model for Enhanced Images

In the past few years, extensive image quality metrics have been proposed, which are mostly based on the measurement of structural distortions [14]. However in real-word applications, the perceived quality is generally determined by many different aspects, which also holds for enhanced images. As a result, measuring structural distortions only is not sufficient for enhanced images, which will be demonstrated in the experiment section. Non-structural factors are also needed [32].

With these observations, we propose a new NR quality metric for enhanced images by measuring non-structural information, sharpness and naturalness. For non-structural aspects, we use color, contrast, luminance and entropy. Sharpness is used to measure structural quality. Finally, natural scene statistics (NSS) features are included for measuring global naturalness.

3.1 Non-structural features

In this paper, five non-structural features are measured, including color consistency, colorfulness, goodness of contrast, luminance and entropy, which are denoted by $S_1 = \{f_1, f_2, f_3, f_4, f_5\}$. These features are employed to capture the non-structure issues in the overall quality of enhanced images. While contrast and luminance have been extensively used in the traditional IQA models, color has been often overlooked, which is an important attribute of real-world images [33].

3.1.1 Color consistency

In high quality images, color is natural and consistent. Over- and under- enhancements tend to cause inconsistency of color distributions. Here, the ratio of abnormal hue (RAH) [34] in an image is adopted to measure color consistency. For an image with size *M´N* in RGB color space, it is first converted into the HSI space. Then the hue channel is used to compute the RAH feature as follows:

$$f_1 = RAH = \frac{|H_{abn}|}{MN}, \tag{1}$$

where $|H_{abn}|$ denotes the number of pixels with abnormal hue. A pixel is regarded to have abnormal hue if its hue value is different from those of its 8´8 neighboring pixels [34].

3.1.2 Colorfulness

High quality images tend to be more colorful, so colorfulness is an important attribute of images. Here, we employ the Color Colorfulness Index (CCI) [35] as the second color feature. The CCI index is defined in an opponent color space RG-YB:

$$RG = R - G, YB = \frac{1}{2}(R + G) - B. \tag{2}$$

With the RG-YB space, the CCI index is calculated as:

$$f_2 = CCI = \sigma_{RGYB} + 0.3 \cdot \mu_{RGYB}, \tag{3}$$

with $\sigma_{RGYB} = \sqrt{\sigma_{RG}^2 + \sigma_{YB}^2}$, $\mu_{RGYB} = \sqrt{\mu_{RG}^2 + \mu_{YB}^2}$, where σ_{RG}^2, σ_{YB}^2 denote the variances of RG and YB, and μ_{RG}, μ_{YB} represent their corresponding mean values.

3.1.3 Contrast

Contrast enhancement has been extensively studied in image enhancement. The goodness of image contrast can be a very important factor of image quality. Image contrast can be approximately described using image histogram. An image with good contrast is expected to have uniform histogram distribution. Therefore, the distance/similarity between a real histogram and the ideal uniform histogram can be used as a measurement of goodness of image contrast. In this work, the Kullback-Leibler divergence is adopted to compute the contrast feature [36]:

$$f_3 = D_{KL}(P, U) = \sum_x P(x) \ln \frac{P(x)}{U(x)} \tag{5}$$

where P and U denote the histogram distributions of a query image and the ideal uniform distribution.

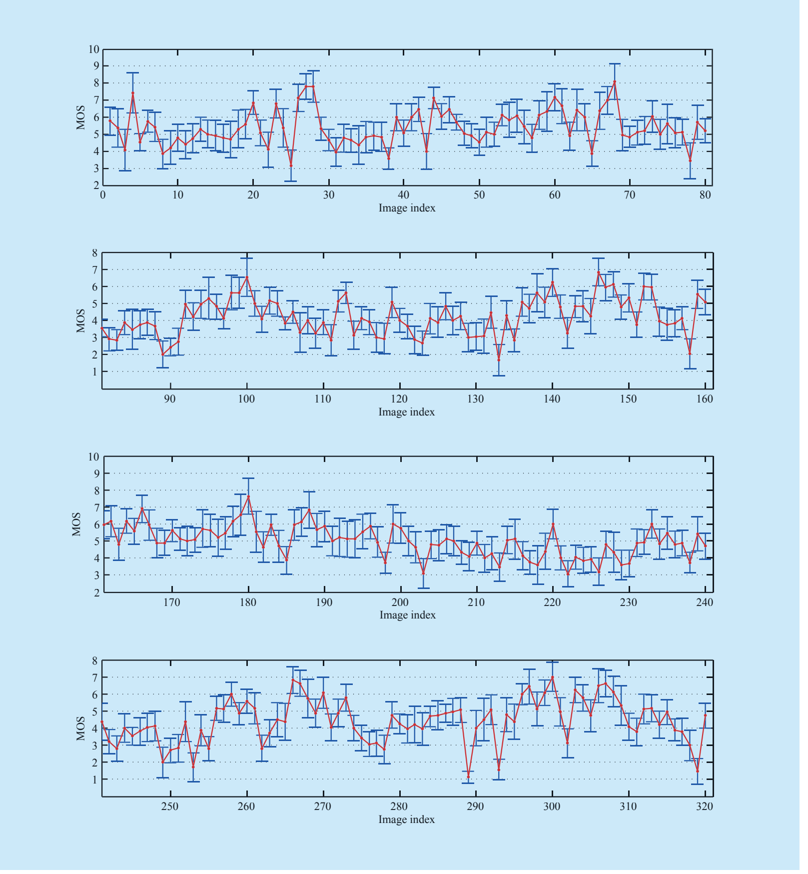

Fig.4 *MOS values of the enhanced images and the corresponding standard deviations*

3.1.4 Luminance

In image enhancement, both under- and over- enhancements cause image luminance uncomfortable. So a measurement of image luminance is needed. In this work, we employ the locally weighted luminance value as the measurement of luminance quality [36]:

$$f_4 = Q_L = I_{avg} \times C_L \tag{6}$$

where I_{avg} denotes the average pixel value, and C_L denotes the Michelson contrast:

$$C_L = \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}}, \tag{7}$$

where $I_{\max}$ and $I_{\min}$ denotes the maximum and minimum intensity values. In implementation, the luminance feature C_L is computed block-wisely. Specifically, the original image is first partitioned into non-overlapping blocks, and the luminance features are obtained. The final feature is calculated as the mean of the values of all blocks.

3.1.5 Entropy

Entropy measures the amount of information in an image. Typically, a high-quality image has bigger entropy value, which can be changed by the presence of distortions. Here image entropy is utilized as the final non-structural feature:

$$f_5 = ENT = -\sum_i P(i)\log_2 P(i), \tag{8}$$

where $P(i)$ denotes the probability of occurrence of an intensity value, and $i \in \{0, 1, 2, ..., 255\}$.

3.2 Sharpness

In the perception of image quality, sharpness is always a key factor. This applies to all kinds of images. In the literature, many no-reference image sharpness metrics have been reported. In this work, we employ our recent work on blind image blur evaluation [37] to calculate the sharpness feature f_6, which has been shown effective for both simulated and real blurred images. More details on the blur assessment method can be found in [37].

3.3 Naturalness

Naturalness is another important criterion of image quality. A high-quality image is expected to be natural. Distortions lead to loss of naturalness in images. In the IQA community, natural scene statistics have been extensively employed for quality assessment with very promising results. In this paper, we adopt the 36 NSS features of the BRISQUE model [38] for measuring overall naturalness of enhanced images, which are denoted by $\{f_7, f_8, \cdots f_{42}\}$. These NSS features are extracted based on the Mean Subtracted Contrast Normalized (MSCN) coefficients, which follow the generalized Gaussian distribution. For further details of the NSS features, readers are referred to [38].

3.4 SVR-based quality prediction

With the aforementioned quality-aware perceptual features, we employ the support vector regression (SVR) [39] to train a quality model. For a query image, the quality can be predicted using the trained SVR model. In our implementation, the Radial Basis Function (RBF) is used as the SVR kernel.

IV. Experimental Results

4.1 Evaluation protocols

In this section, experiments are conducted to demonstrate the effectiveness of the proposed quality model. To this end, several image quality databases are tested, including the proposed Enhanced Image Database EID, Digitally Retouched Image Quality database (DRIQ) [31], Camera Image Database (CID2013) [40] and LIVE in the wild database (LIVE WILD) [41]. EID and DRIQ are specifically designed for image enhancement quality assessment, and CID2013 and LIVE WILD are built for quality assessment of real-world camera images. The DRIQ database consists of 26 original images and the corresponding 78 retouched images, which are obtained using Photoshop by adjusting contrast, sharpness, brightness, color, or combination of these properties of the original images. CID2013 database contains 474 color images captured by 79 imaging devices, i.e., consumer cameras and mobile phones. The LIVE WILD database consists of 1162 authentically distorted images that are captured from many diverse mobile devices.

Three widely adopted criteria are adopted to evaluate metric performances, including Pearson Linear Correlation Coefficient (PLCC), Spearman Rank order Correlation

Coefficient (SRCC) and Root Mean Squared Error (RMSE). PLCC and RMSE are used to measure prediction accuracy, and SRCC is used to measure prediction monotonicity. Before computing them, a five-parameter logistic mapping is performed between the subjective and objective scores:

$$f(x) = \tau_1 \left(\frac{1}{2} - \frac{1}{1 + e^{\tau_2 (x - \tau_3)}} \right) + \tau_4 x + \tau_5 \quad (9)$$

where τ_i, $i = 1, 2, \cdots, 5$, are the parameters to be fitted.

4.2 Results and comparisons

In our experiments, 80% of the images are randomly selected for training, and the remaining 20% images are used for test. The training-test process is repeated by 1000 times, and the median values are used as the performance results. The performance of the proposed method is also compared with the state-of-the-art NR image quality metrics, including BIQI [42]，BLIINDS-II [43]，BRISQUE [38], CORNIA [44], DESIQUE [45], DIIVINE[46], IL-NIQE [47], NFERM [48], NIQE [49], QAC [50] and SSEQ [51].Three contrast enhancement quality metrics are also included for comparison, including FR metrics RIQMC [52] and PCQI [20]，and NR metric [19]. The experimental results are summarized in Tables I-IV.

It is known from Tables I and II that the proposed method achieves the best performances in EID and DRIQ, two databases specifically designed for image enhancement. Furthermore, it significantly outperforms the other compared metrics. These results are not surprising, because almost all the current quality metrics are based on the measurement of structural distortions, which are not the dominated distortions in image enhancement. In other words, non-structural distortions play a more important role in the quality assessment of enhanced images.

The proposed method can also be used for the quality evaluation of images captured by real-word consumer type cameras. The three components of the proposed method also characterize the attributes of camera images. In order to verify the effectiveness of using the proposed method for camera image quality assessment, we test it on two recently released camera image databases, i.e., CID2013 and LIVE WILD. Tables III-IV list the experimental results. It should be noted that in these two databases reference images are not available, so the performance of our method is only compared with the NR quality metrics.

It is known from Tables III-IV that the proposed method also achieves the best per-

Table I *Performances of IQA metrics in EID database*

Metric	Type	PLCC	SRCC	RMSE
BIQI	NR	0.2860	0.1723	1.1489
BLIINDS2	NR	0.1713	0.0861	1.1813
BRISQUE	NR	0.3122	0.2039	1.1393
CORNIA	NR	0.4359	0.3985	1.0791
DESIQUE	NR	0.2928	0.2191	1.1465
DIIVINE	NR	0.2905	0.2711	1.1473
IL-NIQE	NR	0.2287	0.1413	1.1586
NFERM	NR	0.3144	0.322	1.1298
NIQE	NR	0.3288	0.2721	1.1323
QAC	NR	0.2863	0.0542	1.1403
SSEQ	NR	0.1052	0.0867	1.1837
RIQMC	FR	0.2458	0.1524	1.1537
PCQI	FR	0.1621	0.0406	1.1745
Fang [19]	NR	0.2001	0.2151	1.1661
Proposed	NR	0.7448	0.6930	0.7701

Table II *Performances of IQA metrics in DRIQ database*

Metric	Type	PLCC	SRCC	RMSE
BIQI	NR	0.1925	0.1286	2.0026
BLIINDS2	NR	0.1121	0.1761	2.0268
BRISQUE	NR	0.3366	0.3359	1.9206
CORNIA	NR	0.0923	0.0826	2.0309
DESIQUE	NR	0.2920	0.2715	1.9507
DIIVINE	NR	0.3612	0.1661	1.9020
IL-NIQE	NR	0.0158	0.0330	2.0394
NFERM	NR	0.2778	0.2756	1.9593
NIQE	NR	0.3734	0.3428	1.8921
QAC	NR	0.3480	0.3533	1.9121
SSEQ	NR	0.3106	0.2935	1.9391
RIQMC	FR	0.4087	0.3503	1.8615
PCQI	FR	0.6727	0.5987	1.5091
Fang [19]	NR	0.1566	0.1501	2.0144
Proposed	NR	0.8790	0.8531	0.9512

Table III *Performances of IQA metrics in CID2013 database*

Metric	Type	PLCC	SRCC	RMSE
BIQI	NR	0.7282	0.7186	15.4659
BLIINDS2	NR	0.3584	0.2476	21.0679
BRISQUE	NR	0.4704	0.4384	19.9140
CORNIA	NR	0.6736	0.6268	16.6792
DESIQUE	NR	0.5142	0.4813	19.3550
DIIVINE	NR	0.5486	0.5397	18.8682
IL-NIQE	NR	0.4200	0.3021	20.4798
NFERM	NR	0.6259	0.6107	17.6005
NIQE	NR	0.6640	0.6517	16.8732
QAC	NR	0.0681	0.0238	22.5144
SSEQ	NR	0.3683	0.3380	21.9811
Fang [19]	NR	0.1203	0.1149	22.4028
Proposed	NR	0.8164	0.8001	12.4769

Table IV *Performances of IQA metrics in LIVE WILD database*

Metric	Type	PLCC	SRCC	RMSE
BIQI	NR	0.2653	0.2797	20.2965
BLIINDS2	NR	0.1785	0.1271	19.9716
BRISQUE	NR	0.3601	0.3124	18.9345
DESIQUE	NR	0.4086	0.3784	18.5251
DIIVINE	NR	0.4711	0.4655	17.9036
IL-NIQE	NR	0.5024	0.4391	17.5491
NFERM	NR	0.3780	0.3090	18.7902
NIQE	NR	0.4966	0.4510	17.6271
QAC	NR	0.1668	0.2025	20.0123
SSEQ	NR	0.2404	0.2049	19.7013
Fang [19]	NR	0.2390	0.1690	19.7084
Proposed	NR	0.6600	0.6418	15.1953

Table V *Performances of different components of the proposed model in EID database*

Component	PLCC	SRCC	RMSE
Non-structural information	0.5620	0.5044	0.9588
Sharpness	0.2795	0.2933	1.1429
Naturalness	0.6549	0.6049	0.8694
All	0.7448	0.6930	0.7701

formances in camera image databases in terms of both prediction accuracy and monotonicity. Similarly, the performance values are significantly better than those of the compared metrics.

4.3 Contributions of different components

In order further to know the relative contributions of the three components of the proposed metric, we conduct another experiment in EID database. Specifically, the non-structural information, sharpness and naturalness are separately used to test the performance in EID database. Then the results are compared with the overall model. By this means, we can know the relative importance of the components. Table V summarizes the simulation results.

It is known from Table V that the non-structural features and naturalness contribute more on the overall performance, while image sharpness plays a less important role. A combination of all three components delivers the best performance. This further verifies the rationality and effectiveness of the proposed quality model.

V. Conclusions

In this paper, we have addressed the quality evaluation of digitally enhanced images, an important yet much less investigated problem. We have built an enhanced image database based on five image enhancement algorithms and three image processing softwares. Subjective test has been conducted to collect the ground truth of human scores. With the consideration that the current distortion-based quality metrics are very limited in the quality evaluation of enhanced images, we have proposed a new quality metric for enhanced images by simultaneously measuring non-structural information, sharpness and naturalness. We have evaluated the performance of the proposed method on two image enhancement databases and two camera image databases. The experimental results and comparisons have confirmed the effectiveness and advantages of the proposed quality model. As future work, we will use the proposed model for benchmarking and perceptual optimization of image enhancement algorithms.

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