EMPIRICAL EVALUATION OF FULL-REFERENCE IMAGE QUALITY METRICS ON MDID DATABASE

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ABSTRACT

In this study, our goal is to give a comprehensive evaluation of 32 state-of-the-art FR-IQA metrics using the recently published MDID. This database contains distorted images derived from a set of reference, pristine images using random types and levels of distortions. Specifically, Gaussian noise, Gaussian blur, contrast change, JPEG noise, and JPEG2000 noise were considered.

Keywords Full-reference image quality assessment

1 Introduction

The goal of objective image quality assessment is to design mathematical models that are able to predict the perceptual quality of digital images. The classification of objective image quality assessment algorithms is based on the accessibility of the reference image. In the case of reference image is unavailable image quality assessment is considered as a no-reference (NR) one. Reduced-reference (RR) methods have only partial information about the reference image, while full-reference (FR) algorithms have full access to the reference image.

The research of objective image quality assessment demands databases that contain images with the corresponding MOS values. To this end, a number of image quality databases have been made publicly available. Roughly speaking, these databases can be categorized into three groups. The first one contains a smaller set of pristine, reference digital images and artificially distorted images derived from the pristine images considering different artificial distortions at different intensity levels. The second group contains only digital images with authentic distortions collected from photographers, so pristine images cannot be found in such databases. Virtanen *et al.* [1] were first to introduce this type of database for images by releasing CID2013. As a consequence, the development of FR methods is connected to the first group of databases. In contrast Waterloo Exploration [2] and KADIS-700k [3] databases are meant to provide an alternative evaluation of objective image quality assessment models, by means of paired comparisons. That is why, they contain a set of reference (pristine) images, distorted images, and distortion levels. In contrast to other databases, they do not provide MOS values. Information about major publicly available image quality assessment databases are summarized in Table 1.

In this study, we provide a comprehensive evaluation of 32 full-reference image quality assessment (FR-IQA) algorithms on MDID database. In contrast to other available image quality databases, the images in MDID contain multiple types of distortions simultaneously.

The rest of this study is organized as follows. There are a number of publicly available image quality databases, such as IVC [4], LIVE IQA [5], A57 [6], Toyoma [7], TID2008 [8], CSIQ [9], IVC-LAR [10], MMSP 3D [11], IRSQ [12], [13], TID2013 [14], CID2013 [1], LIVE In the Wild [15], Waterloo Exploration [2], MDID [16], KonIQ-10k [17], KADID-10k [18], and KADIS-700k [18]. In Section 2, we give a brief introduction to each of them. In Section 3, we give a comprehensive evaluation of 31 full-reference image quality assessment (FR-IQA) algorithms on MDID database. Finally, a conclusion is drawn in Section 4.

2 Image quality databases

IVC¹ [4] database consists of 10 pristine images, and 235 distorted images, including four types of distortions (JPEG, JPEG2000, locally adaptive resolution coding, blurring). Quality score ratings (1 to 5) are provided in the form of MOS.

LIVE Image Quality Database² (LIVE IQA) [5] has two releases, Release 1 and Release 2. Laboratory for Image and Video Engineering (University of Texas at Austin) conducted an extensive experiment to obtain scores from human subjects for a number of images distorted with different distortion types. Release 2 has more distortion types — JPEG (169 images), JPEG2000 (175 images), Gaussian blur (145 images, White noise (145 images), bit errors in JPEG2000 bit stream (145 images). The subjective quality scores in this database are DMOS (Differential MOS), ranging from 0 to 100.

A57 Database³ [6] has 3 pristine images, and 54 distorted images, including six types of distortions (JPEG, JPEG2000, JPEG2000 with dynamic contrast-based quantization, quantization of the LH subbands of DWT, additive Gaussian white noise, Gaussian blurring). Quality score ratings (0 to 1) are provided in the form of DMOS.

Toyoma Database [7] consists of 14 pristine images, and 168 distorted images, including two types of distortions (JPEG, JPEG2000). Quality score ratings (1 to 5) are provided in the form of MOS.

Tampere Image Database 2008⁴ (TID2008) [8] contains 25 reference images and 1,700 distorted images (25 reference images $\times 17$ types of distortions $\times 4$ levels of distortions). The MOS was obtained from the results of 838 experiments carried out by observers from three countries. 838 observers have performed 256,428 comparisons of visual quality of distorted images or 512,856 evaluations of relative visual quality in image pairs. Higher value of MOS (0 - minimal, 9 - maximal, MSE of each score is 0.019) corresponds to higher visual quality of the image. A file enclosed "mos.txt" contains the Mean Opinion Score for each distorted image.

Computational and Subjective Image Quality⁵ (CSIQ) [9] database consists of 30 original images, each distorted using one of six types of distortions, each at four to five different levels of distortion. The images were subjectively rated based on a linear displacement of the images across four calibrated monitors placed side-by-side with equal viewing distance to the observer. The database contains 5,000 subjective ratings from 35 different — both male and female — observers. Quality score ratings (0 to 1) are provided in the form of DMOS.

IVC-LAR⁶ [10] database contains 8 pristine images (4 natural images and 4 art images), and 120 distorted images, consisting of three types of distortions (JPEG, JPEG2000, locally adaptive resolution coding). Quality score ratings (1 to 5) are provided in the form of MOS.

Wireless Imaging Quality⁷ (WIQ) Database [19], [20] consists of 7 reference images and 80 distorted images. The subjective quality scores are given in DMOS, ranging from 0 to 100.

In contrast to other publicly available image quality databases **MMSP 3D Image Quality Assessment Database**⁸ [11] consists of stereoscopic images with a resolution of $1,920 \times 1,080$ pixels. Specifically, 10 indoor and outdoor scenes were captured with a wide variety of colors, textures, and depth structures. Furthermore, 6 different stimuli have been considered corresponding to different camera distances (10, 20, 30, 40, 50, and 60 cm) for each scene.

Image Retargeting Subjective Quality⁹ (IRSQ) Database [12], [13] consists of 57 reference images grouped into four attributes, specifically face and people, clear foreground object, natural scenery, and geometric structure. Moreover, ten different retargeting methods (cropping, seam carving, scaling, shift-map editing, scale and stretch, etc.) are applied to generate retargeted images. In total, 171 test images can be found in this database.

Tampere Image Database 2013¹⁰ (TID2013) [14] contains 25 reference images and 3,000 distorted images (25 reference images $\times 24$ types of distortions $\times 5$ levels of distortions). MOS (Mean Opinion Score) is provided as subjective score, ranging from 0 to 9.

¹http://www2.irccyn.ec-nantes.fr/ivcdb/

²http://www.live.ece.utexas.edu/research/quality/subjective.htm

³http://vision.eng.shizuoka.ac.jp/mod/page/view.php?id=26

⁴http://www.ponomarenko.info/tid2008.htm

⁵http://vision.eng.shizuoka.ac.jp/mod/page/view.php?id=23

⁶http://ivc.univ-nantes.fr/en/databases/LAR/

⁷https://computervisiononline.com/dataset/1105138665

⁸https://mmspg.epfl.ch/downloads/3diqa/

⁹http://ivp.ee.cuhk.edu.hk/projects/demo/retargeting/index.html

¹⁰http://www.ponomarenko.info/tid2013.htm

The **CID2013**¹¹ [1] database contains 474 images with authentic distortions captured by 79 imaging devices, such as mobile phones, digital still cameras, and digital single-lens reflex cameras.

LIVE In the Wild Image Quality Challenge Database¹² [15] contains widely diverse authentic image distortions on a large number of images captured using a representative variety of modern mobile devices. The LIVE In the Wild Image Quality Database has over 350,000 opinion scores on 1,162 images evaluated by over 8,100 unique human observers.

Waterloo Exploration¹³ [2] database consists of 4,744 reference images and 94,880 distorted images created from them. Instead of collecting MOS for each test image, the authors introduced three alternative test criteria to evaluate the performance of IQA models, such as discriminability test (D-test), listwise ranking consistency test (L-test), and pairwise preference consistency test (P-test).

In contrast to other databases considering artificial distortions, **MDID**¹⁴ [16] obtains distorted images from reference images with random types and levels of distortions. In this way, each distorted image contains multiple types of distortions simultaneously. Gaussian noise, Gaussian blur, contrast change, JPEG noise, and JPEG2000 noise were considered.

The main challenge in applying state-of-the-art deep learning methods to predict image quality in-the-wild is the relatively small size of existing quality scored datasets. The reason for the lack of larger datasets is the massive resources required in generating diverse and publishable content. In **KonIQ-10k**¹⁵ [17] a new systematic and scalable approach is presented to create large-scale, authentic image datasets for image quality assessment. KonIQ-10k [17] consists of 10,073 images, on which large scale crowdsourcing experiments has been carried out in order to obtain reliable quality ratings from 1,467 crowd workers (1.2 million ratings) [21]. During the test users exhibiting unusual scoring behavior were removed.

KADID-10k¹⁶ [18] consists of 81 pristine images and 10, 125 distorted images derived from the pristine images considering 25 different distortion types at 5 intensity levels ($10, 125 = 81 \times 25 \times 5$). In contrast, **KADIS-700k** [18] contains 140,000 pristine images and distorted images were derived using 25 different distortion types at 5 intensity levels but MOS values are not given in this database.

3 Experimental results

The evaluation of objective visual quality assessment is based on the correlation between the predicted and the groundtruth quality scores. Pearson's linear correlation coefficient (PLCC) and Spearman's rank order correlation coefficient (SROCC) are widely applied to this end. Furthermore, some authors give the Kendall's rank order correlation coefficient as well.

The PLCC between data set A and B is defined as

$$PLCC(A,B) = \frac{\sum_{i=1}^{n} (A_i - \overline{A})(B_i - \overline{B})}{\sqrt{\sum_{i=1}^{n} (A_i - \overline{A})^2} \sqrt{\sum_{i=1}^{n} (B_i - \overline{B})^2}},$$
(1)

where \overline{A} and \overline{B} stand for the average of set A and B, A_i and B_i denote the *i*th elements of set A and B, respectively. For two ranked sets A and B SROCC is defined as

$$SROCC(A,B) = \frac{\sum_{i=1}^{n} (A_i - \hat{A})(B_i - B)}{\sqrt{\sum_{i=1}^{n} (A_i - \hat{A})^2} \sqrt{\sum_{i=1}^{n} (B_i - \hat{B})^2}},$$
(2)

where \hat{A} and \hat{B} are the middle ranks of set A and B. KROCC between dataset A and B can be calculated as

$$KROCC(A, B) = \frac{n_c - n_d}{\frac{1}{2}n(n-1)},$$
(3)

where n is the length of the input vectors, n_c is the number of concordant pairs between A and B, and n_d is the number of discordant pairs between A and B.

¹¹http://www.helsinki.fi/psychology/groups/visualcognition/

¹²http://live.ece.utexas.edu/research/ChallengeDB/

¹³ https://ece.uwaterloo.ca/ k29ma/exploration/

¹⁴https://www.sz.tsinghua.edu.cn/labs/vipl/mdid.html

¹⁵http://database.mmsp-kn.de/koniq-10k-database.html

¹⁶http://database.mmsp-kn.de/kadid-10k-database.html

Table 1: Major publicly available image quality assessment databases. Publicly available image quality databases can
be divided into three groups. The first one contains a smaller set of reference images and artificially distorted images
are derived from them using different noise types at different intensity levels. There are also databases which contains
only pristine images, distorted images, and distortion levels without MOS.

Database	Year	Reference images	Test images	Distortion type	Subjective score
IVC [4]	2005	10	235	artificial	MOS (1-5)
LIVE IQA [5]	2006	29	779	artificial	DMOS (0-100)
A57 [6]	2007	3	54	artificial	DMOS (0-1)
Toyoma [7]	2008	14	168	artificial	MOS (1-5)
TID2008 [8]	2008	25	1,700	artificial	MOS (0-9)
CSIQ [9]	2009	30	866	artificial	DMOS (0-1)
IVC-LAR [10]	2009	8	120	artificial	MOS (1-5)
WIQ [19], [20]	2009	7	80	artificial	DMOS (0-100)
MMSP 3D [11]	2009	9	54	artificial	MOS (0-100)
IRSQ [12], [13]	2011	57	171	artificial	MOS (0-5)
TID2013 [14]	2013	25	3,000	artificial	MOS (0-9)
CID2013 [1]	2013	8	474	authentic	MOS (0-9)
LIVE In the Wild [15]	2016	-	1,162	authentic	MOS (1-5)
Waterloo Exploration [2]	2016	4,744	94,880	artificial	-
MDID [16]	2017	20	1600	artificial	MOS (0-8)
KonIQ-10k [17]	2018	-	10,073	authentic	MOS (1-5)
KADID-10k [3]	2019	81	10,125	artificial	MOS (1-5)
KADIS-700k [3]	2019	140,000	700,000	artificial	-

We collected 31 FR-IQA metrics whose source codes are available online. Furthermore, we reimplemented SSIM CNN¹⁷ [45] in MATLAB R2019a. In Table 2, we present PLCC, SROCC, and KROCC values measured over the MDID database. It can be clearly seen from the results that there is still a lot of space for the improvement of FR-IQA algorithms because only HaarPSI [30] was able to produce PLCC and SROCC values higher than 0.9. Furthermore, only three methods — FSIM [28], FSIMc [28], HaarPSI [30] — were able to produce KROCC values higher than 0.7.

4 Conclusion

First, we gave information about the mostly applied image quality databases. Subsequently, we extensively evaluated 32 state-of-the-art FR-IQA methods on MDID database whose images contain multiple types of distortions simultaneously. We dmonstrated that there is still a lot of space for the improvement of FR-IQA algorithms because only HaarPSI [30] was able to produce PLCC and SROCC values higher than 0.9.

¹⁷https://github.com/Skythianos/Pretrained-CNNs-for-full-reference-image-quality-assessment

Method	Year	PLCC	SROCC	KROCC
BLeSS-SR-SIM [22]	2016	0.7535	0.8148	0.6258
BLeSS-FSIM [22]	2016	0.8193	0.8467	0.6576
BLeSS-FSIMc [22]	2016	0.8527	0.8827	0.7018
CBM [23]	2005	0.7367	0.7212	0.5306
CSV [24]	2016	0.8785	0.8814	0.6998
CW-SSIM [25]	2009	0.5900	0.6148	0.4450
DSS [26]	2015	0.8714	0.8661	0.6793
ESSIM [27]	2013	0.6694	0.8253	0.6349
FSIM [28]	2011	0.8591	0.8870	0.7074
FSIMc [28]	2011	0.8639	0.8902	0.7122
GMSD [29]	2013	0.8544	0.8617	0.6797
HaarPSI [30]	2018	0.9051	0.9028	0.7340
MAD [9]	2010	0.7439	0.7243	0.5327
MCSD [31]	2016	0.8386	0.8457	0.6622
MDSI ('mult') [32]	2016	0.8130	0.8278	0.6441
MDSI ('sum') [32]	2016	0.8249	0.8363	0.6527
MS-SSIM [33]	2003	0.7884	0.8292	0.6360
MS-UNIQUE [34]	2017	0.8604	0.8712	0.6893
NQM [35]	2000	0.6177	0.5869	0.4143
PerSIM [36]	2015	0.8282	0.8196	0.6296
PSNR-HVS [37]	2006	0.679	0.6637	0.4845
PSNR-HVS-M [38]	2007	0.6875	0.6739	0.4944
QILV [39]	2006	0.3296	0.4592	0.3214
QSSIM [40]	2011	0.8022	0.8014	0.6074
RFSIM [41]	2010	0.7035	0.6758	0.4884
SCIELAB [42]	1997	0.2552	0.1232	0.0824
SR-SIM [43]	2012	0.7948	0.8517	0.6683
SSIM [44]	2004	0.5798	0.5761	0.4105
SSIM CNN [45]	2018	0.8706	0.8804	0.6992
SUMMER [46]	2019	0.7427	0.7343	0.5434
UQI [47]	2002	0.2175	0.3608	0.2476
VSI [48]	2014	0.7883	0.8570	0.6710

Table 2: Performance comparison of 31 FR-IQA algorithms on MDID database.

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