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

A PREPRINT

Domonkos Varga
Department of Networked Systems and Services
Budapest University of Technology and Economics

October 8, 2019

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

IVC [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 Database [5] (LIVE IQA) 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 Database [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 2008 [8] (TID2008) contains 25 reference images and 1,700 distorted images (25 reference images × 17 types of distortions × 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 Quality (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-LAR [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 Quality (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 [11] consists of stereoscopic images with a resolution of 1,920 × 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 Quality (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 2013 [14] (TID2013) contains 25 reference images and 3,000 distorted images (25 reference images × 24 types of distortions × 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://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 CID201 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 Database** [12] 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 Exploration** [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** [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** [17], a new systematic and scalable approach is presented to create large-scale, authentic image datasets for image quality assessment. KonIQ-10k 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). During the test users exhibiting unusual scoring behavior were removed.

**KADID-10k** [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. In contrast, **KADIS-700k** [18] consists of 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 ground-truth 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

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

where $\bar{A}$ and $\bar{B}$ 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

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

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

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

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 $B$.

---

11. [http://www.helsinki.fi/psychology/groups/visualcognition/](http://www.helsinki.fi/psychology/groups/visualcognition/)
12. [http://live.ece.utexas.edu/research/ChallengeDB/](http://live.ece.utexas.edu/research/ChallengeDB/)
13. [https://ece.uwaterloo.ca/~k29ma/exploration/](https://ece.uwaterloo.ca/~k29ma/exploration/)
14. [https://www.sz.tsinghua.edu.cn/labs/vipl/mdid.html](https://www.sz.tsinghua.edu.cn/labs/vipl/mdid.html)
15. [http://database.mmsp-kn.de/koniq-10k-database.html](http://database.mmsp-kn.de/koniq-10k-database.html)
16. [http://database.mmsp-kn.de/kadid-10k-database.html](http://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 contain 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 [11] | 2013 | 8                | 474         | authentic       | MOS (0-9)        |
| LIVE In the Wild [15]| 2016| -               | 1,162       | authentic       | MOS (1-5)        |
| Waterloo Exploration [12]| 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 CNN [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 demonstrated 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.

https://github.com/Skythianos/Pretrained-CNNs-for-full-reference-image-quality-assessment
Table 2: Performance comparison of 31 FR-IQA algorithms on MDID database.

| 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 |

References

[1] Toni Virtanen, Mikko Nuutinen, Mikko Vahteranoksa, Pirkko Oittinen, and Jukka Hukkanen. Cid2013: A database for evaluating no-reference image quality assessment algorithms. *IEEE Transactions on Image Processing*, 24(1):390–402, 2014.

[2] Kede Ma, Zhengfang Duanmu, Qingbo Wu, Zhou Wang, Hongwei Yong, Hongliang Li, and Lei Zhang. Waterloo exploration database: New challenges for image quality assessment models. *IEEE Transactions on Image Processing*, 26(2):1004–1016, 2017.

[3] Hanhe Lin, Vlad Hosu, and Dietmar Saupe. Kadid-10k: A large-scale artificially distorted iqa database. In *2019 Tenth International Conference on Quality of Multimedia Experience (QoMEX)*, pages 1–3. IEEE, 2019.

[4] Patrick Le Callet and Florent Autrusseau. Subjective quality assessment irccyn/ivc database, 2005. http://www.irccyn.ec-nantes.fr/ivcdb/.

[5] Hamid R Sheikh, Muhammad F Sabir, and Alan C Bovik. A statistical evaluation of recent full reference image quality assessment algorithms. *IEEE Transactions on Image Processing*, 15(11):3440–3451, 2006.

[6] Damon M Chandler and Sheila S Hemami. Vsnr: A wavelet-based visual signal-to-noise ratio for natural images. *IEEE transactions on image processing*, 16(9):2284–2298, 2007.

[7] Sylvain Tourancheau, Florent Autrusseau, Parvez Sazzad, and Yuukou Horita. Impact of the subjective dataset on the performance of image quality metrics. In *IEEE International Conference on Image Processing 2008. ICIP 2008.*, 2008.
[8] Nikolay Ponomarenko, Vladimir Lukin, Alexander Zelensky, Karen Egiazarian, Marco Carli, and Federica Battisti. Tid2008-a database for evaluation of full-reference visual quality assessment metrics. *Advances of Modern Radioelectronics*, 10(4):30–45, 2009.

[9] Eric Cooper Larson and Damon Michael Chandler. Most apparent distortion: full-reference image quality assessment and the role of strategy. *Journal of Electronic Imaging*, 19(1):011006, 2010.

[10] Florent Autrusseau and Marie Babel. Subjective quality assessment of lar coded art images, 2009. http://www.irccyn.ec-nantes.fr/autrusse/Databases/.

[11] Lutz Goldmann, Francesca De Simone, and Touradj Ebrahimi. Impact of acquisition distortion on the quality of stereoscopic images. In *Proceedings of the International Workshop on Video Processing and Quality Metrics for Consumer Electronics*, number MMSPL-CONF-2009-022, 2010.

[12] Lin Ma, Weisi Lin, Chenwei Deng, and King Ngi Ngan. Image retargeting quality assessment: A study of subjective scores and objective metrics. *IEEE Journal of Selected Topics in Signal Processing*, 6(6):626–639, 2012.

[13] Lin Ma, Weisi Lin, Chenwei Deng, and King N Ngan. Study of subjective and objective quality assessment of retargeted images. In *Circuits and Systems (ISCAS), 2012 IEEE International Symposium on*, pages 2677–2680. IEEE, 2012.

[14] Nikolay Ponomarenko, Oleg Ieremeiev, Vladimir Lukin, Karen Egiazarian, Lina Jin, Jaakko Astola, Benoit Vozel, Kacem Chehdi, Marco Carli, Federica Battisti, et al. Color image database tid2013: Peculiarities and preliminary results. In *Visual Information Processing (EUVIP), 2013 4th European Workshop on*, pages 106–111. IEEE, 2013.

[15] Deepti Ghadiyaram and Alan C Bovik. Massive online crowdsourced study of subjective and objective picture quality. *IEEE Transactions on Image Processing*, 25(1):372–387, 2015.

[16] Wen Sun, Fei Zhou, and Qingmin Liao. Mdid: A multiply distorted image database for image quality assessment. *Pattern Recognition*, 61:153–168, 2017.

[17] Hanhe Lin, Vlad Hosu, and Dietmar Saupe. Koniq-10k: Towards an ecologically valid and large-scale iqa database. *arXiv preprint arXiv:1803.08489*, 2018.

[18] Hanhe Lin, Vlad Hosu, and Dietmar Saupe. Kadid-10k: A large-scale artificially distorted iqa database. In *2019 Eleventh International Conference on Quality of Multimedia Experience (QoMEX)*, pages 1–3. IEEE, 2019.

[19] Ulrich Engelke, Maulana Kusuma, Hans-Jürgen Zepernick, and Manora Caldera. Reduced-reference metric design for objective perceptual quality assessment in wireless imaging. *Signal Processing: Image Communication*, 24(7):525–547, 2009.

[20] Ulrich Engelke, Hans-Jürgen Zepernick, and Tubagus Maulana Kusuma. Subjective quality assessment for wireless image communication: The wireless imaging quality database. In *International Workshop on Video Processing and Quality Metrics for Consumer Electronics (VPQM)*. VPQM, 2010.

[21] Dietmar Saupe, Franz Hahn, Vlad Hosu, Igor Zingman, Masud Rana, and Shujun Li. Crowd workers proven useful: A comparative study of subjective video quality assessment. In *QoMEX 2016: 8th International Conference on Quality of Multimedia Experience*, 2016.

[22] Dogancan Temel and Ghassan AlRegib. Bless: Bio-inspired low-level spatiochromatic similarity assisted image quality assessment. In *2016 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–6. IEEE, 2016.

[23] Xinbo Gao, Tao Wang, and Jie Li. A content-based image quality metric. In *International Workshop on Rough Sets, Fuzzy Sets, Data Mining, and Granular-Soft Computing*, pages 231–240. Springer, 2005.

[24] Dogancan Temel and Ghassan AlRegib. Csv: Image quality assessment based on color, structure, and visual system. *Signal Processing: Image Communication*, 48:92–103, 2016.

[25] Mehul P Sampat, Zhou Wang, Shalini Gupta, Alan Conrad Bovik, and Mia K Markey. Complex wavelet structural similarity: A new image similarity index. *IEEE transactions on image processing*, 18(11):2385–2401, 2009.

[26] Amnon Balanov, Arik Schwartz, Yair Moshe, and Nimrod Peleg. Image quality assessment based on dct subband similarity. In *2015 IEEE International Conference on Image Processing (ICIP)*, pages 2105–2109. IEEE, 2015.

[27] Xuande Zhang, Xiangchu Feng, Weixi Wang, and Wufeng Xue. Edge strength similarity for image quality assessment. *IEEE Signal processing letters*, 20(4):319–322, 2013.

[28] Lin Zhang, Lei Zhang, Xuanqin Mou, and David Zhang. Fsim: A feature similarity index for image quality assessment. *IEEE transactions on Image Processing*, 20(8):2378–2386, 2011.
[29] Wufeng Xue, Lei Zhang, Xuanqin Mou, and Alan C Bovik. Gradient magnitude similarity deviation: A highly efficient perceptual image quality index. *IEEE Transactions on Image Processing*, 23(2):684–695, 2013.

[30] Rafael Reisenhofer, Sebastian Bosse, Gitta Kutyniok, and Thomas Wiegand. A haar wavelet-based perceptual similarity index for image quality assessment. *Signal Processing: Image Communication*, 61:33–43, 2018.

[31] Tonghan Wang, Lu Zhang, Huizhen Jia, Baosheng Li, and Huazhong Shu. Multiscale contrast similarity deviation: An effective and efficient index for perceptual image quality assessment. *Signal Processing: Image Communication*, 45:1–9, 2016.

[32] Hossein Ziaei Nafchi, Atena Shahkolaei, Rachid Hedjam, and Mohamed Cheriet. Mean deviation similarity index: Efficient and reliable full-reference image quality evaluator. *IEEE Access*, 4:5579–5590, 2016.

[33] Zhou Wang, Eero P Simoncelli, and Alan C Bovik. Multiscale structural similarity for image quality assessment. In *The Thirtieth Seventh Asilomar Conference on Signals, Systems & Computers*, 2003, volume 2, pages 1398–1402. IEEE, 2003.

[34] Mohit Prabhushankar, Dogancan Temel, and Ghassan AlRegib. Ms-unique: Multi-model and sharpness-weighted unsupervised image quality estimation. *Electronic Imaging*, 2017(12):30–35, 2017.

[35] Niranjan Damera-Venkata, Thomas D Kite, Wilson S Geisler, Brian L Evans, and Alan C Bovik. Image quality assessment based on a degradation model. *IEEE transactions on image processing*, 9(4):636–650, 2000.

[36] Dogancan Temel and Ghassan AlRegib. Persim: Multi-resolution image quality assessment in the perceptually uniform color domain. In *2015 IEEE International Conference on Image Processing (ICIP)*, pages 1682–1686. IEEE, 2015.

[37] Karen Egiazarian, Jaakko Astola, Nikolay Ponomarenko, Vladimir Lukin, Federica Battisti, and Marco Carli. New full-reference quality metrics based on hvs. In *Proceedings of the Second International Workshop on Video Processing and Quality Metrics*, volume 4, 2006.

[38] Nikolay Ponomarenko, Flavia Silvestri, Karen Egiazarian, Marco Carli, Jaakko Astola, and Vladimir Lukin. On between-coefficient contrast masking of dct basis functions. In *Proceedings of the third international workshop on video processing and quality metrics*, volume 4, 2007.

[39] Santiago Aja-Fernandez, Raul San Jose Estepar, Carlos Alberola-Lopez, and Carl-Fredrik Westin. Image quality assessment based on local variance. In *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 4815–4818. IEEE, 2006.

[40] Amir Kolaman and Orly Yadin-Pecht. Quaternion structural similarity: a new quality index for color images. *IEEE Transactions on Image Processing*, 21(4):1526–1536, 2011.

[41] Lin Zhang, Lei Zhang, and Xuanqin Mou. Rfsim: A feature based image quality assessment metric using riesz transforms. In *2010 IEEE International Conference on Image Processing*, pages 321–324. IEEE, 2010.

[42] Xuemei Zhang, D Amnon Silverstein, Joyce E Farrell, and Brian A Wandell. Color image quality metric s-cielab and its application on halftone texture visibility. In *Proceedings IEEE COMPCON 97. Digest of Papers*, pages 44–48. IEEE, 1997.

[43] Lin Zhang and Hongyu Li. Sr-sim: A fast and high performance iqa index based on spectral residual. In *2012 19th IEEE international conference on image processing*, pages 1473–1476. IEEE, 2012.

[44] Zhou Wang, Alan C Bovik, Hamid R Sheikh, Eero P Simoncelli, et al. Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing*, 13(4):600–612, 2004.

[45] Seyed Ali Amirshahi, Marius Pedersen, and Azeddine Beghdadi. Reviving traditional image quality metrics using cnns. In *Color and Imaging Conference*, volume 2018, pages 241–246. Society for Imaging Science and Technology, 2018.

[46] Dogancan Temel and Ghassan AlRegib. Perceptual image quality assessment through spectral analysis of error representations. *Signal Processing: Image Communication*, 70:37–46, 2019.

[47] Zhou Wang and Alan C Bovik. A universal image quality index. *IEEE signal processing letters*, 9(3):81–84, 2002.

[48] Lin Zhang, Ying Shen, and Hongyu Li. Vsi: A visual saliency-induced index for perceptual image quality assessment. *IEEE Transactions on Image Processing*, 23(10):4270–4281, 2014.