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Quadratic Fitting Model in No-Reference Image Quality Assessment

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***Abstract* — The perceptual quality of image is affected by distortions during compression, delivery and storage. Distortions also impact automatic image quality assessment (IQA) that needs to be highly correlated with subjective scores. In the absence of reference, which is a typical scenario in practice, no-reference (NR) metrics are necessary for quality measurements. Recently such methods are proposed, and they employ natural scene statistics (NSS). The experimental analysis performed in this paper takes into consideration two fitting or regression models of several NR-IQA metrics relying on different distortion types. The results show quadratic model as promising for making relations in terms of difference mean opinion score and Shannon entropy.**

***Keywords* — Image Quality Assessment, no-reference, fitting model, correlation, subjective score, Shannon entropy.**

I. Introduction

FITTING or regression tasks are inevitable for making good correlations in the image quality assessment (IQA) research. Recently, there has been a significant advancement in quality measurements, particularly those based on machine learning. The proposed IQA methods should satisfy the growing demand for efficient image quality evaluation regardless of the level of present distortions. No-reference (NR) IQA methods are of great importance since they do not require a reference image, usually of the highest quality, which is in practice unavailable. Thus, NR-IQA is valuable for an expanding range of purposes including visual quality-based measurements. In the case of practical implementations for visual applications and services, imaging and video industries, Internet and social networks, reference content is not obtainable, so reliable, non-expensive and efficient NR-IQA approaches are necessary [1]-[3].

For estimation of IQA metric, human end users are taken into account. Namely, they are considered as the proper evaluators of visual quality, so subjective scores are acquired within IQA research. This is usually done in control laboratory circumstances. Even though careful preparation is required, many factors affect giving ratings by human. It is assumed that no one is better than end consumers to support objective findings. On the other hand, there is a human factor and it contributes to possible errors. Still in state-of-the-art experiments, this is profoundly useful for proposing new metrics [3]-[5].

Moreover, this is supported by relatively novel research which makes comparisons between automatically obtained objective values on one side and averaged or mean opinion scores (mos) on the other. The highest value at the mos range represents an image of the highest quality, with no impairment registered. Difference mos or dmos can help evaluations in determining how much introduced distortions will affect viewers meaning how much will they notice the difference. In assessing image quality, they are collected as opinion scores. The proposed IQA metric selection is regarded as a good fit compared to the opinion scores. Also, the International Telecommunication Union (ITU) consider3 different models for objective quality evaluation like ITU-T P.1203, ITU-T P.1204, and similar, as well as for subjective measurements like ITU-R BT.500, ITU-T P.910, etc [6]. Perceptual adjustments are possible as well as human factor effects. Good correlation results between an objective metric and opinion score lead to possibility of replacing time-consuming subjective assessment when it is required. Keeping this in mind the same rules for subjective scores apply to most efficient metrics, especially the blind ones, like Shannon Entropy (SE) [7]-[9].

This paper addresses linear and quadratic fitting related to different types of distortions compared to both subjective scores and SE. For the purpose of analysis, the publicly available dataset called LIVE database [10] is used since it consists of a proper collection of images for IQA tests. Moreover, it includes several common distortions [4].

The main concept or idea is to observe linear and quadratic models to achieve a better relation between objective and subjective scores. The paper is organized as follows. After the introduction, the next section, Section II

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is dedicated to NR-IQA and NSS based metrics. Typical distortions are then tested in Section III by making correlations with corresponding dmos values and by taking into account three common NR metrics. Two fittings are tested. This is followed by making correlations for various content. Also, SE has been tested for making comparison between linear and quadratic regression model. The obtained results are presented in Section IV with appropriate discussion. At the end of this paper, the results are summarized and new possibilities for future work are mentioned.

II. Image Quality Assessment and No-Reference metrics

Image Quality Assessment (IQA) models have an important role in modern applications, services and systems. Designing a suitable IQA means to provide a quantitative estimate for image quality in terms of perceptual evaluation. Development of objective IQA model that can automatically give a single numerical value that corresponds to subjective evaluation has gained considerable attention in the research community and industrial field [7]-[9]. Regardless of distortion type or level, arbitrary content should be adequately rated.

There are three main directions of research depending on the reference. The first direction is oriented towards having a full reference for comparison to distorted image. IQA can be Full-Reference (FR) if distortion-less content is available. In this manner, it is easy to monitor distortion degree like noise level introduced to contaminate image [2]-[4]. Another direction for objective evaluation is Reduced-Reference (RR), which has a challenge of applying limited information related to reference. RR-IQA is needed when reference image is not fully available, but there is some prior knowledge about reference attributes. The third direction in the research represents No-Reference (NR) metrics. This metric category is of particular importance since an end user receives only distorted image without any knowledge about reference [1], [5]. This is a typical blind approach and leads to the requirement for NR-IQA for practical applications. Three IQA metric categories are represented in Fig.1.

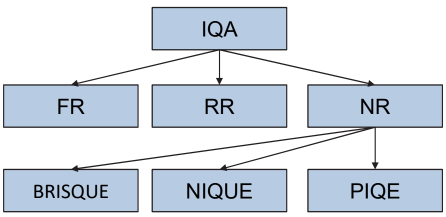

Fig. 1. IQA quality metrics.

Even in the case of NR-IQA it is necessary to learn from monitoring the degree of deterioration to establish image quality. Until now, it has been progressing slowly [5]. Novel NR-IQA methods employ machine learning, and they have been attracting considerable interest in recent years. Although interpretation of human perception is a challenging task, several very efficient methods are proposed for NR-IQA, like [7]-[8], [11]-[12]:

- BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator),
- NIQE (Naturalness Image Quality Evaluator), and
- PIQE/PIQUE (Perception based Image Quality Evaluator).

What unites them is that the above-mentioned metrics are based on statistical features related to so called natural scene statistics (NSS) [11].

A. NR-IQA methods

NR-IQA based methods like BRISQUE, NIQE and PIQE are of importance since they offer low-complexity, but efficient solutions for the most challenging NR quality estimation. Feature engineering has been directed towards NSS, and numerous application support the efficiency of NSS based metrics [11]-[14]. Moreover, due to various distortion sources and types, findings may lead to inconsistencies.

BRISQUE method is developed by employing image dataset with different kinds of known distortions and recognized types of distortion. Additionally, the model is cognizant of opinions, so the metric is opinion-aware determined using computed variance and human judgment quality ratings. In the absence of distortion-free image, it is questionable which types and combinations of distortions should be considered. Thus, BRISQUE may produce different outcomes depending on data used for training procedure, i.e. distortions found in the dataset.

Another method similar to BRISQUE is the NIQE approach. In order to avoid BRISQUE method's high dependencies on distortions employed in the training and opinions, NIQE introduces the opposite. Namely, the training process is performed for original images of high quality, meaning clean images without distortions. In addition, subjective scoring is avoided in the implementation leading to an opinion-unaware metric. This all may cause uncertainties compared to BRISQUE producing less correlation with perceptual scoring. A quality-aware set of statistical characteristics are the basis for this metric, where reference images without distortions have certain regularities in its content and where deviations are monitored according to statistics in IQA.

The third mentioned NR-IQA metric is PIQE, which is an opinion-unaware method. It represents an unsupervised approach, where image quality is determined via block-wise distortion estimation. Similar results as with NIQE are expected. This index does not require training and models human perception using psycho-visual attributes.

B. Natural scene statistics and metrics

The BRISQUE, NIQE and PIQE are typical NR-IQA algorithms intended for various distortions. They are based on NSS with specific framework.

Typically, the framework, described briefly, consists of two sections. In the first section, a block-wise algorithm tends to classify blocks based on uniformity. Each block is classified as uniform or non-uniform in order to find potential active locations. The likelihood of distortions present in an image is estimated. This is followed by the section where likelihood-weighted sum is offered as a final grade. The sum is calculated consistently with distortions, as in algorithm for the computation of Blind Image Quality Index [12], [15]. For comprehending and assessing vision, the measurement of natural scenes is highlighted [16]-[18]. The attribute of natural statistics is applied in NR-IQA methods, which are block-oriented, i.e. assessment algorithms that are locally used. When the image is separated using blocks, through local examination via NSS it is possible to evaluate quality according structure and present distortions in spatial domain. With the intention of NSS features implementation in [8] the preprocessing step is applied. During the preprocessing local normalized luminance is discovered by mean subtraction and normalizing. The normalization is performed as:

$$I_{norm}(i,j)=\frac{I(i,j)-\mu(i,j)}{\sigma(i,j)+C}, \tag{1}$$

where I is intensity image, I_{norm} is normalized version, C is a constant to prevent any potential instability, and i and j are corresponding spatial indices. Parameters μ and σ are calculated via circularly symmetric Gaussian weighting function w prepared for two-dimensional application:

$$\mu(i,j)=\sum_{m}\sum_{n} w_{m,n} I_{m,n}(i,j), \tag{2}$$

$$\sigma(i,j)=\sqrt{\sum_{m}\sum_{n} w_{m,n}\left(I_{m,n}(i,j)-\mu(i,j)\right)^2}, \tag{3}$$

where w is usually of order $k=7$ ($k=m=n$). This can be considered as a transform that is applied locally in order to obtain so called mean subtracted contrast normalized (MSCN) coefficients. The MSCN coefficients are suitable since the resulting distribution can be modeled as generalized Gaussian distribution (GGD). This GGD model enables to get two parameters and to perform further investigations related to local distortions by applying machine learning such as regression using the support vector regressor (SVR) [15]. Using GGD modeling or similar approaches it is possible to obtain scale-invariance and to characterize images via NSS [11], [19]- [21]. If a distorted image shows in any way disparate statistics locally, it can be treated adequately. For example, additional components like noise can be described by some distribution that can be useful for NR-IQA. Having the efficient approach for obtaining GGD coefficients in mind, the researchers have been able to use various domains in NSS implementation. The most straightforward, but efficient approach is available in BRISQUE method where spatial domain is applied [8]. Other metrics use a similar way to identify the level of distortion present in an image. For example, DIVINE metric [12] implements wavelet sub-band coefficients as an alternative of domain. Another example is BLINDS-II metric presented in [21] where coefficients in DCT (Discrete Cosine Transform) domain are used. DCT is applied locally for the GGD modeling and IQA, where the results seem to compete with the standard FR metric such as SSIM (Structural Similarity Index Measure) from the perceptual point of view [21].

C. Distortions and perceptual quality

The proper selection of NR-IQA metric should show a high correlation with judgment scores obtained during subjective evaluation. Nevertheless, they depend on distortions existing in an image. The automatically obtained result using an objective method should be sensitive to present distortions, which is challenging.

A distortion can be described as any modification applied to image making the non-identical two-dimensional result. The features of modified original or non-distorted image can be affected in a positive or negative manner. Due to this, methods can be categorized according to the considered modification type. Therefore, the metrics can target certain changes/distortions, or the model can be more general [12].

Distortions can come from a variety of sources. Typical modifications that occur in available models are related to compression (e.g. JPEG (Joint Photographic Experts Group) or JPEG2000/JPEG2k), common noise of well-known distributions, filtering like low-pass filtering (blurring), transmission distortions, etc. One of the publicly available datasets applied as a reference for NR-IQA is LIVE dataset [4], [10]. In such a dataset, twenty-nine undistorted original images are available, as well as distortion versions categorized into groups labeled as: jp2k, jpeg, wn, gblur, ff. With jp2k and jpeg are represented different levels of JPEG2000 and JPEG distortions, respectively. White noise (wn), Gaussian based blurring (gblur) and fast-fading (ff) are the available categories as well. This is illustrated in Fig.2 for image *bikes.bmp.*

Fig. 2. Reference/original image *bikes.bmp* with corresponding versions categorized according to distortion type (jp2k, jpeg, wn, gblur, ff).

Low-level features extracted from distorted image need to be sensitive to considered distortion types behaving similar to common human perception. Datasets for IQA are therefore enriched with subjective scores expressed via mos or dmos. In the LIVE database dmos values can be found for the experimental analysis, where an objective metric should show similar behavior represented usually through correlation. If proper fit is obtained it may provide enormous resource savings. For quality analysis in controlled testing setup, for example, the subjective scores are necessary and the assessment of a large number of observers is required. The approach is too slow in practical applications, frequently costly, and cumbersome.

NSS features found in NR-IQA metrics should be able to identify traits susceptible to particular sorts of distortions. There are other approaches and features in addition to GGD [20], where other distributions can be useful as well. Among the methods there is also dmos distribution modeling, where greater length of feature vector is used or where novel classifiers, distortion and image type combinations are tested, etc. [16]-[21].

III. Experimental analysis

The distortion-awareness or opinion-awareness of a metric is considered while developing NR-IQA method. Better results are expected for opinion-aware methods, since correlations with subjective scores are used as reliable judgment. End users apply these metrics as ready-made solutions, while human perceptual assessment can be different. If scores collected in the controlled environment are taken from LIVE database [4], [10] they can be seen as benchmark for NR-IQA.

The subjective quality scores are presented throughout dmos for images of length 982 (including reference images), where the histogram with fourteen bins for dmos of only distorted images are shown in Fig.3. Totally five types of distortions of twenty-nine bmp images are analyzed here: (1) jp2k (JPEG2000 compression), (2) jpeg (JPEG compression), (3) wn (white noise), (4) gblur (Gaussian blur) and (5) ff (fast fading using the Rayleigh channel). The histogram is presented for all five-distortion types. Three NR-IQA metrics: BRISQUE, NIQE and PIQE, are tested here. A common feature vector of length thirty six is applied per block for NSS implementation. Block size is 96×96 pixels, while two scales are applied for obtaining the final feature vector (eighteen features per each scale).

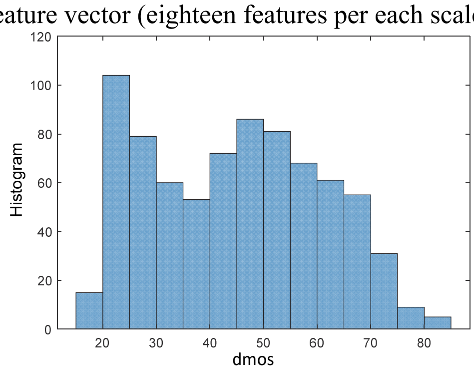

Fig. 3. Histogram of dmos subjective scores for five distortion types.

Experimental analysis if the three metrics consists of three steps. In the first step common linear regression is tested for each distortion type separately in order to evaluate fitting model, Namely, the model is tested according to relative measure of fitting model (R-squared or R^2) and absolute measure of fit (RMSE - Root Mean Square Error). Both measures provide information on how well a chosen model fits. While matching with dmos values, linear and quadratic fitting are tested for comparison between the two measures for each NR-IQA tested method. In the second step, the relative measure is applied for further comparison and evaluation of how each distortion type acts. For the worst distortion results three correlation coefficients are calculated per image using the Person, Kendall and Spearman technique for the purpose of finding image outliers that mostly affect results. The third step is dedicated to analysis of distorted images in the case of Shannon entropy (SE) implementation instead of dmos. Since a human factor exists, it is of interest to have a substitute of dmos when it is not available. Thus, linear and quadratic models are tested in terms of SE and relative information.

IV. Results

The linear regression with each tested distortion is tested for each metric. This is presented for BRISQUE in Fig.4, where high correlation in terms of dmos is obvious. Calculated measures of R-squared and RMSE values for BRISQUE per distortion are presented in Fig.5. Higher values for R-squared and lower RMSE are obtained for quadratic model instead of the liner one. This is especially obvious for jpeg distortion.

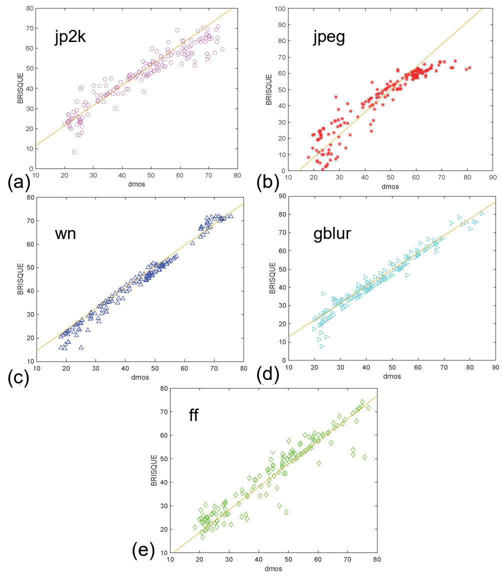

Fig. 4. BRISQUE scores versus dmos values for five types of distortions: (a) jp2k, (b) jpeg, (c) wn, (d) gblur and (e) ff.

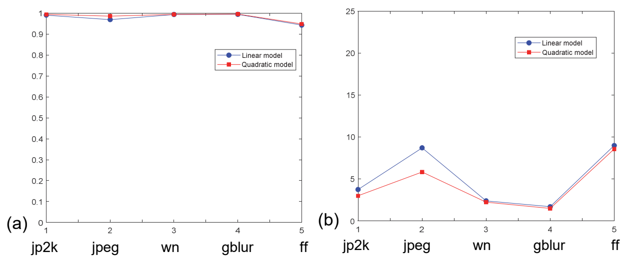

Fig. 5. Calculated (a) R-squared and (b) RMSE values for BRISQUE fitting models per distortion.

Similarly is done for NIQE and PIQE fitting and usage of linear and quadratic models. For these metrics improved results are particularly obtained for the quadratic model in the case of wn and ff. By analyzing the Pearson, Kendal and Spearman correlation results in the second step per image, it is discovered that each case yields a different set of outlier images obtained per method. They are presented in Fig.7 through image index as orange dashed boxes for jpeg and green boxes for ff. Spearman is usually chosen as an intermediate option, but in most cases similar results are obtained for other correlation techniques. Since R-squared results give the relative information, they are compared in terms of dmos showing a significant advantage in wn for the quadratic compared to the linear fitting model. Higher values are obtained for other distortions as well, but with still relatively little progress in jpeg and ff case. The most challenging seems jpeg in NIQE and PIQE (orange boxes in Fig.8), while it is ff in NIQE (green boxes in Fig.8.).

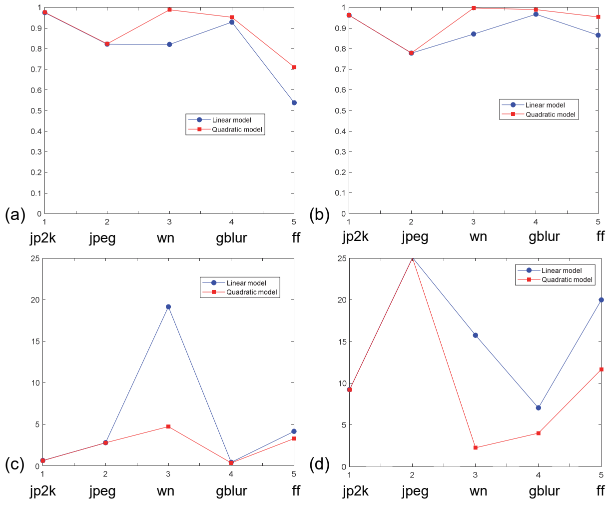

Fig. 6. Calculated R-squared values for: (a) NIQE and (b) PIQE fitting models per distortion calculated RMSE values for: (c) NIQE and (d) PIQE fitting models per distortion.

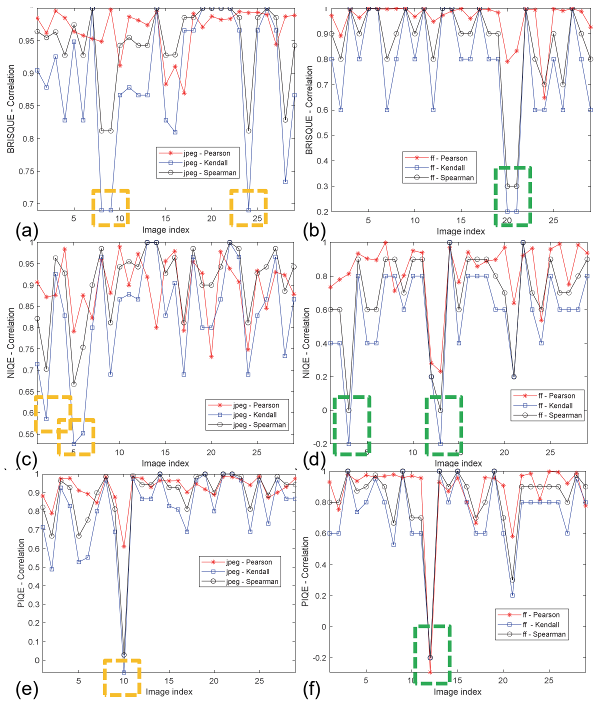

Fig. 7. Correlation coefficients calculated per image using Person, Kendall and Spearman technique for: (a)BRISQUE and jpeg, (b)BRISQUE and ff, (c)NIQE and jpeg, (d)NIQE and ff, (e)PIQE and jpeg, and (f) PIQE and ff distortion in terms of dmos with noted worst results.

In the third step, dmos is replaced with SE in order to observe the fitting results. Here, calculated R-squared values are significantly higher in the quadratic model compared to the linear, which proves the similar behavior as in dmos case. It is interesting to observe that BRISQUE gives the lowest results for jpeg, PIQE for wn and NIQE for ff distortions. Nevertheless, distinctions are more apparent in quadratic modeling. Black boxes in Fig.9 present this, where high correlations with metrics are obtained (values between 0.7 and 1).

The findings lead to a conclusion that if all three metrics are found their median value will result in high correlation in the quadratic model in terms of SE.

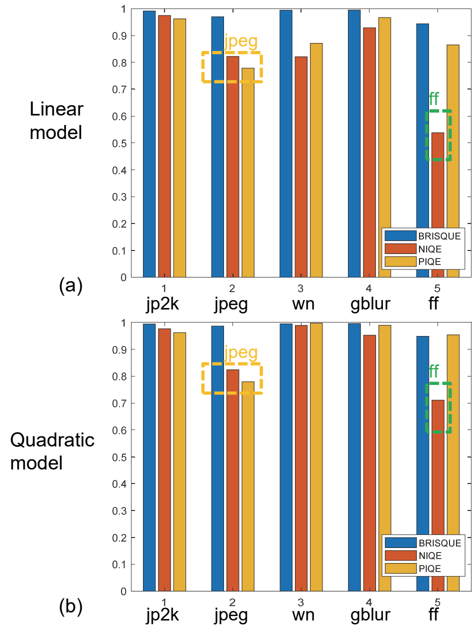

Fig. 8. (a) Linear and (b) quadratic model showing the worst results for jpeg and ff distortions compared to other types in terms of dmos.

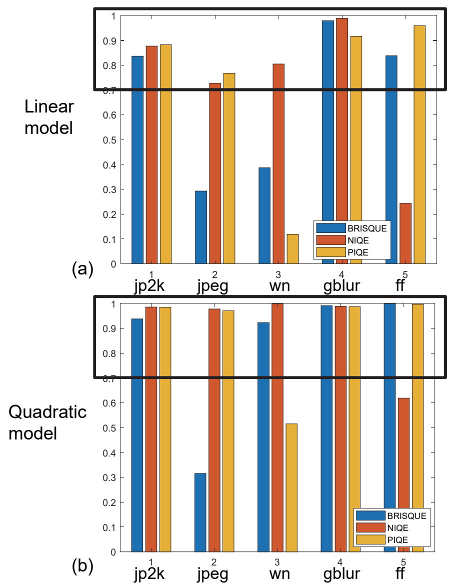

Fig. 9. (a) Linear and (b) quadratic model showing high correlation in black boxes (>0.7) in terms of SE.

TABLE 1: TEST RESULTS OF THE QUADRATIC MODEL FOR SE

N	MODEL	JP2K	JPEG	WN	GBLUR	FF
1	LINEAR	0.8769	0.7271	0.3868	0.9792	0.8379
2	QUADR. MODEL	**0.9849**	**0.9708**	**0.9232**	**0.9887**	**0.9972**
3	Δ_{REL}	12.3	33.5	138.7	1.0	19.0

TABLE 2: THE LEAST CORRELATION FOUND WITH SE

N	DISTORTION	LEAST CORR. WITH SE	SE BASED R^2	DMOS BASED R^2
1	JP2K	BRISQUE	0.9378	0.9945
2	JPEG	BRISQUE	**0.3157**	0.9864
3	WN	PIQE	**0.5151**	0.9973
4	GBLUR	PIQE	0.9873	0.9893
5	FF	NIQE	**0.6188**	0.7109

TABLE 3: TEST RESULTS OF THE IMPLEMENTED QUADRATIC MODEL

N	DISTORTION	SE BASED MEDIAN R^2	SELECTED METRIC	DMOS BASED R^2
1	JP2K	**0.9849**	PIQE	**0.9623**
2	JPEG	**0.9708**	PIQE	**0.7793**
3	WN	**0.9232**	BRISQUE	**0.9949**
4	GBLUR	**0.9887**	NIQE	**0.9525**
5	FF	**0.9972**	PIQE	**0.9541**

V. CONCLUSION

In this paper fitting a performance has been evaluated using three NR-IQA metrics which rely on NSS. These metrics give a single numerical value for quality evaluation, which is considered of great importance, and thus metrics like BRISQUE, NIQE and PIQE are handy and used in many fields. Moreover, these metrics are convenient since they do not depend on reference, i.e. image without distortions, which is often not available in practice. The findings in the performed experimental analysis are based on a dataset that consists of various distortion types and corresponding subjective scores. High correlation of each tested metric with subjective scores presented via dmos exists. Nevertheless, by evaluation of R-squared and RMSE values it can be observed that goodness of fit is different obtaining the worst results with images accompanied with jpeg and ff distortions. This is confirmed for both linear and quadratic fitting model. In addition, by examining the obtained correlation scores it can be concluded that specific content particularly affects statistics based on the correlations with the dmos. The content that provides outliers is not identical for each distortion or quality metric. It is closely connected to the fact that NR-IQA metrics are made to function efficiently with particular distortion types.

The fact that the quadratic fitting model outperforms the linear one for fitting task with dmos is tested in another manner. Having in mind the Shannon entropy representing the information conveyed in the content itself, the examination has been repeated giving similar results as in the dmos case. Outcomes that are produced using correlation with SE instead of dmos showed also different results for each metric and distortion, but the same results in the sense that the quadratic model does better in regard of fitting compared to the linear one.

The tested metrics are machine learning based models, whereas SE differs in that, but can also be regarded as NR-IQA metric. Here, SE of each image is considered as a substitute for the subjective score for the fitting task. It is observed that suitability for applying quadratic model instead of linear is even more apparent. For the majority of tested scenarios, SE is shown as useful when dmos is unavailable, which may be useful for future work.

In the fitting task for both dmos and SE performed within analysis, the quadratic model outperformed the linear one. This leads to the possibility of applying a higher number of parameters meaning a higher degree of freedom in future modeling. The future work will be oriented towards further examinations of distorted images having in mind similar behavior of SE and subjective evaluations and proposing more accurate methods for NR-IQA.

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REFERENCES

[1] A. Gavrovska, D. Dujković, A. Samčović, Y. Golub, and V. Starovoitov, “No-reference local image quality evaluation,” In *30th Telecommunications Forum* (TELFOR), IEEE, pp. 1-4, Nov. 2022.

[2] S. Su, Q. Yan, Y. Zhu, J. Sun, & Y. Zhang, “From distortion manifold to perceptual quality: a data efficient blind image quality assessment approach,” *Pattern Recognition*, *133*, 109047, 2023.

[3] Z. Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli, “Image quality assessment: from error measurement to structural similarity,” *IEEE transactions on image processing*, vol.13, pp. 600-613, 1 January, 2004.

[4] H.R. Sheikh, M.F. Sabir, and A.C. Bovik, “A statistical evaluation of recent full reference image quality assessment algorithms,” *IEEE Transactions on image processing*, *15*(11), pp.3440-3451, 2006.

[5] Z. Wang, and A.C. Bovik, “Reduced-and no-reference image quality assessment,” *IEEE Signal Processing Magazine*, *28*(6), pp. 29-40, 2011.

[6] ITU - the International Telecommunication Union, https://www.itu.int, accessed 01.10.2023.

[7] A. Mittal, R. Soundararajan, and A.C. Bovik, “Making a “completely blind” image quality analyzer,” *IEEE Signal processing letters*, *20*(3), pp.209-212, 2012.

[8] A. Mittal, A.K. Moorthy, and A.C. Bovik, “No-reference image quality assessment in the spatial domain,” *IEEE Transactions on image processing*, *21*(12), pp.4695-4708, December 2012.

[9] O. Ieremeiev, V. Lukin, N. Ponomarenko, and K. Egiazarian, “Combined no-reference IQA metric and its performance analysis”, *Image Processing: Algorithms and Systems XVII*, 2019.

[10] LIVE website: https://live.ece.utexas.edu/research/Quality/, accessed 30.09.2022.

[11] D.L. Ruderman, “The statistics of natural images,”*Network: computation in neural systems*, *5*(4), pp. 517-548, 1994.

[12] A.K. Moorthy, and A.C. Bovik, “Blind image quality assessment: From natural scene statistics to perceptual quality,” *IEEE transactions on Image Processing*, *20*(12), pp. 3350-3364, 2011.

[13] W. Ji, J. Wu, M. Zhang, Z. Liu, G. Shi, and X. Xie, “Blind image quality assessment with joint entropy degradation,” *IEEE Access*, *7*, pp. 30925-30936, 2019.

[14] L. Rong, C.Wang, “Blind Quality Assessment for Multiply-Distorted Images via Distortion Decomposition,” In *Proc. of the 2020 5th Int. Conf. on Multimedia Systems and Signal Processing*, pp. 31-35, May 2022.

[15] S. Bonettinia, G. Franchinia, “Quality measure score predictor for imaging via SVR”, *Proceedings of SIMAI 2023*, 137, 2023.

[16] M. Agarla, L. Celona, R. Schettini, “An efficient method for no-reference video quality assessment,” *Journal of Imaging*, *7*(3), p. 55, 2021.

[17] S. Dost, F. Saud, M. Shabbir, M.G. Khan, M. Shahid, and B. Lovstrom, “Reduced reference image and video quality assessments: review of methods,” *EURASIP Journal on Image and Video Processing*, *2022*(1), pp. 1-31, 2022.

[18] M.H. Pinson, “Why no reference metrics for image and video quality lack accuracy and reproducibility,” *IEEE Transactions on Broadcasting*, *69*(1), pp. 97-117, 2022.

[19] A. Lemesle, A. Marion, L. Roux, and A. Gouaillard, “NARVAL: A no-reference video quality tool for real-time communications,” *Electronic Imaging*, *2019*(12), p. 213-1, 2019.

[20] Z. Tu, C.J. Chen, L.H. Chen, Y. Wang, N. Birkbeck, B. Adsumilli, and A.C. Bovik, “Regression or classification? New methods to evaluate no-reference picture and video quality models,” In *Int. Conf. on Acoustics, Speech and Signal Processing* (ICASSP), pp. 2085-2089, IEEE, June 2021.

[21] M. A. Saad, A. C. Bovik, and C. Charrier, “Blind image quality assessment: A natural scene statistics approach in the DCT domain,” *IEEE Transactions on Image Processing*, *21*(8), pp. 3339-3352, 2012.