COLOR IMAGE DATABASE HTID FOR VERIFICATION OF NO-REFERENCE METRICS: PECULIARITIES AND PRELIMINARY RESULTS

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ABSTRACT

The paper describes a new image database HTID for verification and training of no-reference image visual quality metrics. The database contains 3000 color images of size 1536x1024 pixels cropped from the real-life photos produced by the mobile phone cameras with various shooting and post-processing settings. Mean opinion scores for images of the database are obtained. Peculiarities of the database are considered. A comparative analysis of the sate-of-the-art no-reference image visual quality metrics is carried out. It is shown that the proposed database takes its own unique place in the existing image databases and can be effectively used for metrics' verification.

***Index Terms*—** no-reference image visual quality assessment, mean opinion scores, image databases

1. INTRODUCTION

No-reference image visual quality assessment is an important task actual for imaging systems (digital cameras), for image retrieval systems, for design of image enhancement methods.

Visual quality of an image at the output of a digital camera depends on several factors, including capturing settings and parameters of image post-processing inside the camera. There can be different types of distortions, e.g. blur or motion blur, noise, artifacts of image processing, e.g. noise suppression. On the other hand, there can be also the results of incorrect selection of processing parameters, such as correction of white balance (WB), sharpening, histogram equalization, etc. There can be even results of artificial manipulations with the image to "fool" no-reference metric, e.g. by adding a pattern noise to a blurred image. Therefore, no-reference image quality assessment is a nontrivial task.

The best correspondence with a human perception is provided by metrics based on large deep convolutional classifying networks [1]. These networks are able to take into account not only low-level image characteristics such as noise and blur levels, but also high level characteristics of image quality such as attractiveness of scene elements, quality of scene composition, quality of color composition, etc. However, for effective training of these networks, very large image databases with mean opinion scores (MOS) are needed, which contain millions of such images. Existing databases Koniq-10K [1], FLIVE [2], Live-in-the-Wild [3], NRTID [4], SPAQ [5] contain in total less than 100000 images with MOS, therefore there is a necessity to design new large image databases with MOS. Due to lack of images for training, the databases designed for full-reference metrics' verification such as TID2013 [6] and LIVE [7] are used in practice for no-reference metrics' training and verification.

One of the problems related to training of no-reference metrics based on neural networks is a bad representativeness of existing image databases with MOS, which can be used as a ground-truth data for training. Such image databases as KonIQ-10k [1], FLIVE [2], Live-in-the-Wild [3], NRTID [4] contain many images with blur, images captured in low light conditions, including cases of wrong white balance and noise presence. However, there is a very small number of images with other distortions such as changes in color hue and color saturation, over-sharpening, changes in the dynamic range of luminance component. Also, there are many images in these databases, which visual quality depends on their high-level content (for example, it can be an adorable domestic animal or a pet). It makes sense to train metrics' ability to consider low level image visual quality factors.

Most of the existing large image databases with MOS consists of downscaled images with a large downscaling factor. This downscaling eliminates many real-life distortions present in full size source images (images at output of digital cameras). SPAQ database [5] is positioned as the one containing real-life images from mobile phones, however MOS for this database are collected for downscaled versions of those images. Thus, all published large image databases with MOS contain only greatly downscaled images. It increases quality of images, however, at the same time, decreases the relevance of these images and their correspondence to the real-life distortions.

Another problem which is very time-consuming is collecting of Mean Opinion Scores (MOS). For metrics training based on neural networks, it is desirable to have millions of images with collected MOS. At the same time, to obtain one MOS value, up to 120 judgments should be averaged [1]. This restricts a practical size of the designed image databases by several tens of thousands [1, 2]. Thus, there is a necessity to design more effective methods of collecting MOS values. This should simplify the process of creation of new image databases with MOS.

In the paper, we propose a new large image database HTID, which substantially complements existing large databases increasing overall representativity and effectivity of no-reference metrics training and verification.

Section 2 describes HTID creation. Peculiarities of HTID are considered in Section 3, while effectiveness of HTID for no-reference metrics' verification is estimated in Section 4.

2. HTID DESIGN

2.1 Principles of HTID design

The goal of Huawei Tampere Image Database (HTID) design is to extend the representativeness of existing databases with MOS, bringing into training many real-life distortions and processing results.

HTID contains images taken by different mobile devices (smartphones and tablets). Each test set of the database contains different photos of the same scene from the same point of view, but with different shooting parameters and with different image post-processing settings.

The main requirement was the following: during the capture of photos for a given scene, a camera should be motionless. It is strongly desirable even not to touch the camera until making the last photo in a sequence. So, we have used Camera2 API in Android devices to capture photo sequences with different acquisition parameters in a fully automatic manner.

We have varied the following parameters of camera to obtain different distortions:

- Exposure time
- ISO factor
- Focus distance
- White balance setup
- Denoising setup
- Edge enhancement setup

A random combination of changing parameters is used to obtain a good coverage of the variety of real-life distortions.

Let us give some more details how images were collected.

1) A given mobile phone is tested on the compatibility with Camera 2 API and a possibility to change different shooting parameters.

2) A draft sequence of 200…300 images with different acquiring parameters is formed. All images are formed for the same scene and by a mobile phone fixed by a tripod.

3) We select manually a photo with a best quality and determine which parameters of shooting were used.

4) A final sequence of the same scene is formed, but a photo with parameters of shooting corresponding to the best quality is formed K times, where K = 20…40 depending on the noise level in the best photo.

5) K images corresponding to the best acquired parameters are averaged to suppress a noise. For the outdoor images with a partial object motion (influence of wind, etc.) the averaging is carried out using block matching to avoid a motion blur. Let us call the image "BVQ-image" (best visual quality image).

6) 20…40 images that are visually different from each other (and with different types of distortions) are selected from all images of the set for further processing and obtaining of MOS.

7) Each image of the test set is cropped to the size 1536x1024 and saved in "png" format (without losses).

After capturing and cropping of real-life images and selection of BVQ image for each set, we have applied a list of distortions and processing algorithms to BVQ image.

As a result, 200-300 images are obtained for each draft set.

Only 60 images from each draft set are included into the final set. Some of them are needed to provide a desirable database functionality. A remaining part is selected to provide a better variation of quality factors in the set. We have tried to maximize a difference between images in the set by the following parameters: mean level of the luminance component, a standard deviation of the luminance component, a local variance of the luminance component, a hue of the averaged color (color is averaged in RGB color space), a saturation of the averaged color.

For a convenient metrics' verification and analysis of results, there are the same distortions on the same positions in all 50 sets of HTID. These distortions are listed in Table 1.

Table 1. Distortions and processing settings in each set of HTID

Image in the set	Distortion or processing
#1	BVQ image
#2	Good quality image with a small natural noise
#3, #4	BVQ with adjusted (increased) contrast
#5, #6	Decreased and increased brightness of BVQ
#7, #8, #9	Decreased and increased saturation of BVQ
#10, #11, #12, #13	Change of hue of BVQ
#14, #15	Sharpening of BVQ
#16	Sharpening of image #2
#17, #18, #19, #20, #21	BVQ with different levels of additive Gaussian noise. These images are reference images for linearization of collected MOS
#22, #23	Images #19 and #20 after denoising by DnCNN filter [43]
#24	Result of super resolution x4 by DnCNN of the image #25
#25	BVQ downsampled x4 and upsampled back using bicubic interpolation
#26	BVQ with added Gaussian blur
#27	Image #26 with added small Gaussian noise to increase image acutance
#28 — #60	Images with different natural distortions due to different capturing parameters, images with visible artifacts of JPEG compression, results of BM3D denoising [44], etc.

2.2 Experiments of collecting MOS

For the methodology to obtain MOS used in FLIVE [2], KonIQ-10k [1] and Live-in-the-Wild [3], approximately

100 judgments for each image are needed to obtain a good quality MOS. For 3000 images 300 000 judgments in total are needed.

In TID2013 [6] and NRTID [4], pairwise comparisons of image quality were used to collect MOS. On each step of experiments, observer had to choose an image with a better visual quality from the visualized pair of images. As it was demonstrated in [4, 6], this way of evaluation of image quality is much easier for observers than a quantitative evaluation. This methodology needs approximately 40 observers and 400 000 comparisons of image quality for 3000 images.

To collect MOS for HTID, we have used even faster methodology to obtain MOS, based on the pairwise comparisons of image visual quality and Glicko rating system [8, 9]. This rating system provides both rating of a given image (we will consider it like a MOS analogue) and a current standard deviation of the rating. The methodology was used in [10] to collect MOS for merging of several databases into one large database.

A usage of Glicko rating system significantly speeds up collecting of MOS by the pairwise comparisons due to better selection of the candidates for pairs. As a result, a smaller number of judgments is needed to obtain the same quality of MOS. It allows selecting for a comparison a pair of images, whose standard deviations will be maximally decreased after comparison, or just a pair of images with the closest ratings.

An observer compares a visual quality of a given pair of images and makes a judgment by choosing an image with a better visual quality. According to Glicko rating system, a new rating R_i and a new standard deviation S_i of a given image with an index i after comparison with an image having an index j are calculated as:

$$
\begin{aligned}
R_i' &= R_i + \frac{g(S_j)(v-E)q}{1/S_i^2 + 1/d^2}, \\
S_i' &= \sqrt{(1/S_i^2 + 1/d^2)^{-1}}, \\
g(S) &= \frac{1}{\sqrt{1+3q^2S^2/\pi^2}}, \\
E &= \frac{1}{1+10^{-g(S_j)(R_i-R_j)/400}}, \\
d^2 &= \left(q^2 g(S_j)^2 E(1-E)\right)^{-1}, \\
q &= \frac{\ln 10}{400},
\end{aligned}
\qquad (3)
$$

where R_i' is the new rating of the i-th image, S_i' is the new standard deviation of the i-th image, v is the result of judgment (1 corresponds to a better quality of the i-th image, 0 corresponds to a better quality of the j-th image).

Let us give the basic steps of the proposed algorithm to collect MOS using the pairwise image comparisons and Glicko rating system:

1) Ratings R_i of all images are set equal to 1500. Standard deviations S_i'of all ratings are set equal to 350 (these values are recommended in Glicko rating system [7]). Here i=1...N, where N is the number of images in the test set.

2) For all possible image pairs {i, j}, we calculate the difference Δ(i,j)=S_i+S_j-S_i'-S_j', where S_i' and S_j' are new values of S_i and S_j after the pairwise comparison calculated according to Glicko rating system.

3) A pair of images with a maximal Δ(i,j) is selected and shown to an observer for a judgment.

4) After making a judgment, ratings of both images and their standard deviations are corrected according to (1).

5) Steps 2-4 are repeated until a required quality of ratings (number of judgments or values of standard deviations of ratings) are met.

A window of our software designed for collecting MOS is shown in Fig. 1.

Fig. 1. Software for collecting MOS

A computer mouse click on the image shows a second image in the pair. Another click returns the first image back. Observers chooses the better-looking image and presses "This is better" button. Making judgments for 300 image pairs needs in average 15-20 minutes.

We needed to obtain a mutual MOS for all sets in HTID. Therefore, there were pairs combined from different image sets in our experiments. In total, 55000 judgments (in average, 36 for each image) have been performed by 17 experienced observers. It is 7 times smaller than the number of judgments needed for MOS collecting in [4, 6] to achieve a comparable MOS quality. According to [10], 36 judgments per image are enough to obtain Spearman rank order correlation coefficient (SROCC) value between the collected MOS and the ideal MOS at the level 0.97 or higher.

Table 2 shows the main details of the designed image database.

Table 2. Details of HTID

Number of images	3000 color images of the size 1536x1024 pixels cropped from real life images produced by mobile cameras (without downscaling)
Image sets	50
Number of distortions types	14 synthetic distortion types and natural distortions (random combinations of wrong focus, wrong WB, small exposure time, sharpening, denoising parameters, level of JPEG compression)
MOS collecting	Pairwise image comparisons using Glicko rating system

Number of judgments	55000 (in average, 36 for each image) by 17 experienced observers
MOS range	0..10
Visual quality	Low and medium

3. MAIN PECULIARITIES OF HTID

Fig. 2 shows miniatures of the first images of each test set of HTID. We have included to the database the scenes with different peculiar properties, useful for no-reference metrics' testing. We have tried to facilitate the task of observers making judgments for collecting MOS. For that, we have endeavored to add on each scene an object with color predictable for human perception.

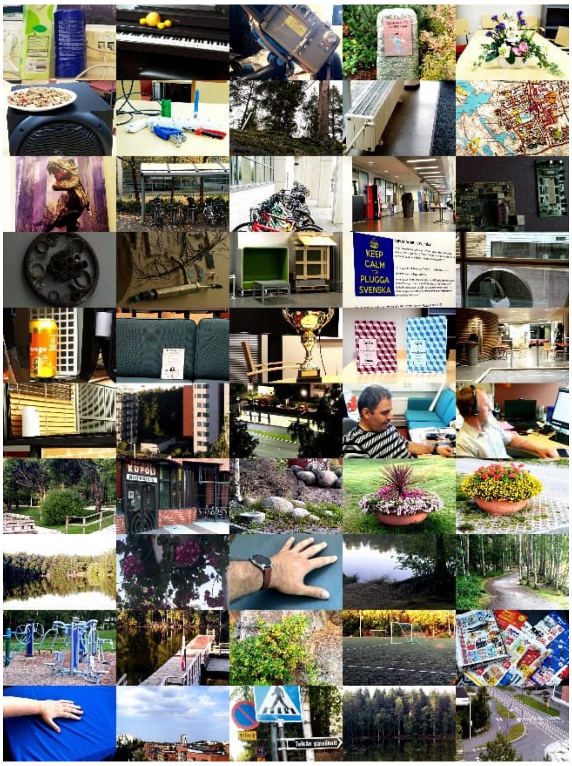

Fig. 2. List of 50 scenes of HTID

At the same time, we strived to complicate the task for image analysis algorithms. For example, there is no gray color in the set # 46 (hand on a blue background). It is difficult for algorithms to determine the correct colors for that scene.

There are also four sets with human skin colors, many outdoor scenes, water surfaces, one night and one sky scene.

We concentrated on making a database with low level image quality factors. So, we avoided to include in the database the scenes with high level quality factors, such as presence of an adorable domestic animal on the photo, etc. High level quality factors often outweigh all other factors and impede metrics training and analysis of obtained results.

The database contains many color distortions. Because of this, we have tried to select scenes for capturing with a presence of at least one object with color predictable for humans.

Fig. 3. Illustration of difficulty of changing of color saturation for visual quality assessment

Fig. 4. Illustration of difficulty of changing color hue for visual quality assessment

Fig. 3 shows image #9 (BVQ with increased color saturation) of the sets #38 and #45. For a human hand, this is a distortion, but for advertising newspapers, it is an enhancement of a visual quality.

Fig. 4 shows another example of difficulty for quality assessment: changing of color hue.

HTID provides many such challenges for no-reference metrics.

Using methodology from [10], we have merged MOS of HTID with MOS of KonIQ-10k, FLIVE, LIVE-in-the-Wild and NRTID databases (see Fig. 5).

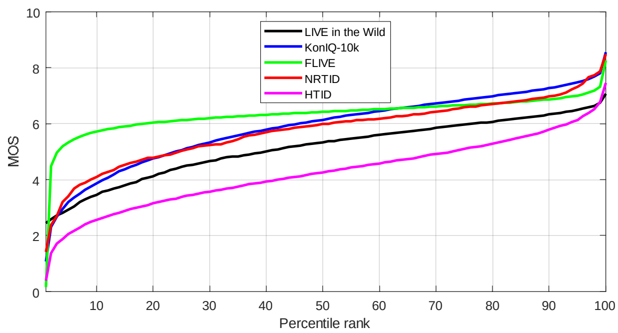

Fig. 5. MOS of HTID merged with MOS of other large image databases

One can see that the images of HTID have low and medium visual quality in comparison to the images of other databases. It allows increasing the quality of training and verification of no-reference metrics for this subrange of image quality.

It is also important to note, that HTID allows excluding high level quality factors from metric verification. Since each subset contains images of the same scene, it is possible to calculate SROCC between MOS and a given metric separately for each subset. In this way, HTID can be effectively used for a verification or training of metrics considering only low level quality factors.

Table 3. SROCC for different subsets of the proposed HTID database

Metric	Subsets of HTID											Whole HTID
	Contrast change	Bright. change	Sat. change	Hue change	Shar-pening	Additive noise	Denoi-sing	SR	Bicubic interp.	Acutance	Natural	
KonCept512[1]	0.76	0.63	0.67	0.53	0.53	0.55	0.69	0.59	0.64	0.92	0.69	0.66
UIQA [25]	0.63	0.50	0.60	0.49	0.46	0.80	0.61	0.27	0.54	0.90	0.59	0.60
ilniqe [28]	0.17	0.33	0.30	0.42	0.55	0.77	0.39	0.37	0.34	0.93	0.62	0.57
Otroshi [26]	0.53	0.57	0.55	0.44	0.35	-0.19	0.57	0.52	0.30	0.91	0.57	0.49
brisque [35]	0.32	0.52	0.51	0.44	0.16	0.66	0.57	-0.65	-0.01	0.89	0.23	0.32
Paq2Pic [2]	0.41	0.64	0.41	0.40	0.42	-1.34	0.49	0.38	0.44	0.91	0.36	0.26
DESIQUE [33]	0.14	0.57	0.43	0.36	0.42	0.12	0.52	-0.90	0.13	0.93	0.04	0.17
FISH [11]	0.42	0.40	0.38	0.36	-0.02	-1.63	0.49	-0.47	0.03	0.44	0.29	0.12
CIEQ [38]	0.42	-0.03	-0.04	-0.19	0.04	0.13	-0.23	-0.28	0.31	0.09	-0.03	-0.02
DIIVINE [27]												
DB-CNN [29]												
ENIQA [30]												
SFA [31]												
NFERM [32]												
Smetric [10]												
Sr metric [34]												
C-DIIVINE [27]												
blur metric [36]												
biqaa [37]												
Niqe [39]												
BIQME [40]												
bliinds2 [41]												
biqi [42]												

4. USAGE OF HTID FOR NO-REFERENCE METRICS VERIFICATION

HTID database contains many types of distortions (or processing results) and there is a possibility to calculate SROCC not only for the whole set, but also for the subsets of HTID.

Let us introduce a partial SROCC for a given subset Q as:

$$SROCC(Q) = 1 - \frac{6\sum_{i\in Q}(R_{1i}-R_{2i})^2}{(n-1)(n-2)\#Q}, \quad (1)$$

where Q is a subset of HTID, R_{1i}, R_{2i} are ranks of the i-th image in HTID MOS (R_1) and verifying metric values (R_2) ordered in the ascending order, n is 3000 (number of images in HTID), $\#Q$ denotes number of elements in Q.

While SROCC values are in the range -1 ... 1, values of partial SROCC might exceed the limits.

Table 3 contains values of different partial SROCC and SROCC for the whole set for some of the existing no-reference image visual quality metrics (we used KonCept512 metric trained on merged databases in [10]). It is clearly seen that HTID is difficult for all existing metrics (the best metric KonCept512 provides SROCC value smaller than 0.7).

Table 3 illustrates that the proposed HTID is useful not only for metrics' verification, but also for metrics design as well. For example, it is clearly seen that Paq2Pic metric performs in a very wrong way in the presence of an intensive additive noise, providing negative correspondence to human perception.

As it is stated in Section 3, HTID allows calculating SROCC separately for each subset and average the values, excluding high level factors (difference between scenes) from analysis:

$$SROCC_S = \frac{\sum_{i=1}^{50} SROCC_i}{50}, \quad (2)$$

where $SROCC_i$ is SROCC calculated only for images of i-th set of HTID.

Table 4 contains $SROCC_s$ values for the best five metrics.

Table 4. $SROCC_S$ for best five no-reference metrics

Metric	KonCept512	UIQA	ilniqe	Otroshi	brisque
$SROCC_s$	0.68	0.61	0.59	0.48	0.33

The results are similar to Table 3 but not the same.

CONCLUSIONS

The paper presents a novel image database HTID which improves quality of no-reference metrics verification and training. Methodology of image acquiring and MOS collecting is described. It is shown that the designed HTID database complements well the existing large databases increasing the representativeness of the databases pool and it is difficult for the existing no-reference metrics.

A link to HTID page will be published in the camera-ready paper.

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