COLOR IMAGE DATABASE TID2013: PECULIARITIES AND PRELIMINARY RESULTS

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ABSTRACT

Visual quality of color images is an important aspect in various applications of digital image processing and multimedia. A large number of visual quality metrics (indices) has been proposed recently. In order to assess their reliability, several databases of color images with various sets of distortions have been exploited. Here we present a new database called TID2013 that contains a larger number of images. Compared to its predecessor TID2008, seven new types and one more level of distortions are included. The need for considering these new types of distortions is briefly described. Besides, preliminary results of experiments with a large number of volunteers for determining the mean opinion score (MOS) are presented. Spearman and Kendall rank order correlation factors between MOS and a set of popular metrics are calculated and presented. Their analysis shows that adequateness of the existing metrics is worth improving. Special attention is to be paid to accounting for color information and observers focus of attention to locally active areas in images.

Index Terms— Image visual quality, color image database.

1. INTRODUCTION

In modern applications of digital image processing, visual quality is of a prime importance [1-3]. In this sense, color images attract special attention since they are the main type of data in communications, multimedia, Internet, etc.

Many good full-reference visual quality metrics (also called indices) that take into account specific features of human visual system (HVS) have been already proposed [1-3]. To characterize adequateness and performance of these metrics, several databases of color images with certain types and levels of distortions have been intensively used [4] including the databases LIVE, Toyama, TID2008 [5], etc. These databases have served the main goals of their creation (as well as other supplementary goals) well enough. In particular, the aforementioned and other databases have allowed comparing performance for different full-reference visual quality metrics (see, e.g., [5-8]). The achieved performances have been utilized for a better understanding of drawbacks of the analyzed metrics and stimulated the design of new metrics and/or improvement (modification) of existing ones [6, 9-11]. Besides, the obtained results have allowed to make a proper choice of metrics suited for a particular application (as, e.g., lossy compression or denoising) in the best way. Thus, development of HVS-metrics and advancement of databases for metric verification are in a close loop facilitating each other.

It is worth stressing out that there are two tendencies coexisting in parallel. A first tendency is to design a universal HVS-metric able to perform well for any kind and level of distortions. Understanding difficulties in a design of such a universal metric, some researchers use to fuse (combine) several good HVS-metrics in one or another way [10, 12-14]. Although "world records" can be gained in this way, it also leads to rather complex solutions not always applicable in practice. A second tendency is to design or to choose an application oriented indices of objective image quality assessment [15]. To follow this way, one needs first to verify performance of several HVS-metrics for images with distortion types and levels typical for a given application. Then, a best one, according to a set and priority of requirements for a given application, is to be chosen.

In both cases, there is a need for image databases containing a large number of images, various types (and subsets) of distortions and a rather wide range of distortions levels (intensities) starting from just noticeable and ending by rather annoying that can be met in the worst case. For four years, the image database TID2008 (created and made freely available at the end of 2008) served its designers and many other researchers (there are more than 100 citations of the database and corresponding papers that describe it). In fact, it has become a challenging task to provide high performance of a newly designed metric just for this database (since other databases contain less distorted images and less number of distortion types including quite exotic ones).

However, due to rapid development of multimedia and image communications, new challenges and applications have appeared. Thus, we have decided to make an extended version of TID2008 called TID2013. Some reasons for this are given in the next Section. New types of distortions introduced in TID2013 are briefly discussed in Section 3 alongside with a description of methodology of carried out experiments. Besides, initial results (values of MOS) have been already obtained for this database. Moreover, rank correlation factors have been calculated for initial set of known HVS-metrics. The obtained data are presented in Section 4 also containing a preliminary analysis of observed tendencies.

2. TID2008 BASIC PROPERTIES AND OUTCOMES

Let us recall basic properties of the database TID2008 that has served as a prototype of TID2013. TID2008 contains 25 reference (distortion-free) color images where 24 images are obtained (by cropping), from the Kodak database available at http://r0k.us/graphics/kodak/ and one artificially created (synthetic) image is added to them. All images are of the same fixed size 512x384 pixels to display three images (reference and two distorted ones) at the monitor screen simultaneously. There are also 1700 distorted images in the database where 68 distorted images (four levels for each of seventeen types of distortions) have been obtained for each reference image. Distortions have been mainly simulated in such a way that the first level corresponded to peak signal-to-noise ratio (PSNR) equal to 30 dB and three other levels related to 27, 24, and 21 dB, respectively.

Considered distortion types are the following: additive white Gaussian noise (#1), additive white Gaussian noise which is more intensive in color components than in the luminance component (#2), additive Gaussian spatially correlated noise (#3), masked noise (#4), high frequency noise (#5), impulse noise (#6), quantization noise (#7), Gaussian blur (#8), image denoising (residual noise, #9), JPEG lossy compression (#10), JPEG2000 lossy compression (#11), JPEG transmission errors (#12), JPEG2000 transmission errors (#13), non-eccentricity pattern noise (#14), local block-wise distortions of different intensity (#15), mean shift (#16), contrast change (#17). As one can see, non-traditional distortions types (in particular, ## 14…17) have been modeled and the corresponding images have been included into the database.

The experiments have been carried out in tristimulus manner. Having a reference image and two distorted images displayed simultaneously, an observer was asked to choose a better (higher visual quality) image between two distorted ones. This chosen image got one point. Each distorted image participated in nine comparisons and the winning points were summed-up. The experiment results for all observers were processed with rejecting abnormal ones (outliers that occurred with probability about 2%) and then averaged for each tested image. Thus, the obtained MOS values varied within the limits from 0 to 9, where larger MOS, as the result, relate to a better visual quality assessed.

Certainly, the experiment participants were instructed concerning preferred conditions and a methodology of experiments. Experiments were conducted in three countries (Ukraine, Finland, Italy) and the obtained results were in good agreement (see [16] for more details). Totally 838 experiments were performed allowing to obtain MOS with accuracy higher than for other databases.

Analysis of the obtained results could be performed in many ways. A traditional approach is to determine Spearman or Kendall rank order correlation coefficient (ROCC) [17] between MOS and a given HVS or other metric. This is usually done for all test images and distortion types in the database. However, a reasonable approach in analysis is to determine ROCC values for certain subsets of distortion types. This approach allows determining which type of distortions is “hard” for a given metric or for all known metrics.

For example, experience of exploiting TID2008 has clearly demonstrated that distortion types included into the subset Exotic [16] (## 6, 14, 15) are hard for any metric. For example, the best (largest) values of Spearman ROCC for all types of distortions are larger than 0.8 for the metrics considered in [16] and they exceed 0.85 for the best recently proposed HVS-metrics [7-10]. Meanwhile, the largest values of Spearman ROCC for the subset Exotic for the metrics considered in [16] was about 0.68 and only slightly larger than for such conventional metrics as MSE and PSNR. Later efforts in design of new HVS-metrics have led to increasing Spearman and Kendall ROCCs for subsets that contain such specific types of distortions [9].

Alongside with the types of distortions to which existing HVS-metrics are not adapted well, there are also subsets of distortion types that are characterized by HVS-metrics with high degree of adequateness. For example, the subset called Simple in [9] contains images with distortion types ## 1, 8, 10, 11 (additive white Gaussian noise, Gaussian blur, JPEG and JPEG2000 lossy compression). Spearman ROCC between MOS and the most advanced modern HVS metrics for this subset exceeds 0.93 [9]. This means that a user can easily choose a good metric among the best ones according to Spearman or Kendall ROCC for an application for which the aforementioned types of distortions are expected (e.g., digital photography).

Experience of utilizing TID2008 has resulted in several other important conclusions. Let us briefly recall them. First, spatially correlated noise (distortion type # 3) and quantization noise (#7) are the most annoying among types of distortions often met in practice (under condition of the same PSNR for analyzed images with different types of distortions). Second, residual noise after image denoising

(#9) is perceived similarly to Gaussian blur (#8) and denoised image is often assessed visually not better than original noisy one even if PSNR increases by a few dB [18]. Third, mean shift (#16) practically does not influence perception and evaluation of image visual quality under condition that it is not too large. Meanwhile, moderate contrast enhancement (particular case of distortion type # 17) is often perceived as an improvement of image visual quality.

Besides, since the database TID2008 already contains freely available distorted images, they have been also used for testing and efficiency analysis of blind methods for noise variance estimation [19], color image denoising techniques [18], verification of no-reference metrics [20], etc.

Meanwhile, the use of TID2008 has also demonstrated shortcomings of this database. One of them is that for practically all distorted images the visual difference between a distorted image and corresponding reference image is easily observed. At the same time, analysis of metric performance for situations of just noticeable distortions is desirable [21]. Thus, availability of images with a smaller level of distortions is of interest for databases. Besides, there are several types of distortions that are important in modern practice but the distorted images with them are not present in TID2008. These obstacles have run us to idea of creating a new, modified, database described in the next Section.

3. SOME PECULIARITIES OF TID2013

To get around aforementioned shortcomings of TID2008, we have created on its basis an extended database TID2013 (available at http://ponomarenko.info/tid2013.htm). First of all, images with five levels of distortions (instead of four in TID2008) are present in the database TID2013. For this database, distorted images with PSNR about 33 dB have been generated for all 25 test images with 17 types of distortions earlier present in TID2008. Besides, images with seven new types of distortions (also five levels) have been added.

In fact, choosing new types of distortions to be exemplified in TID2013, we had many options. On one hand, creation of a new database and MOS obtaining for it is not an easy task and new databases for metric verification are designed not often. Thus, having decided to create TID2013, we had to sufficiently modify and to add types of distortions which are really important from theoretical and practical viewpoints. On the other hand, we had to take into account some specific aspects to carry out experiments. First, experiment for each test image should not take too much time to prevent observer's tiredness. Second, the number of distorted images for each reference image has to be even to make each distorted image participating in equal number of visual quality comparisons.

Taking all these into consideration, we have decided to introduce just seven new types of distortions to get the total number of distortion types equal to 24. With five levels of distortions, there are 120 distorted versions of each reference color image now (instead of 68 in TID2008).

The following distortion types have been introduced: change of color saturation (#18), Multiplicative Gaussian noise (#19), Comfort noise (#20), Lossy compression of noisy images (#21), Image color quantization with dither (#22), Chromatic aberrations (#23), Sparse sampling and reconstruction (#24).

As it is seen, three types of distortions in one or another way relate to color (## 18, 22, 23). Including of them has been motivated by the facts that peculiarities of color distortions are not well represented in already existing databases whilst they are very important in modern practice [7, 11, 22], in particular, for color image printing. Note that many existing HVS-metrics are calculated for each component of a color image separately and then aggregated. Thus, they are unable to account for peculiarities of color distortion perception. More in detail, changes in color saturation can result from larger quantization of color components in JPEG compression and JPEG-based algorithms in compression of video [23]. Distortion modeling was carried out after image transformation into YCbCr color space. Distortions "Image color quantization with dither" have been modeled using the Matlab function rgb2ind that converts RGB image to indexed image using dither. The number of quantization levels was adjusted individually to provide a desired PSNR. Chromatic aberrations were modeled by slight mutual shifting of R, G, and B components with respect to each other with further blurring of shifted components.

Multiplicative Gaussian spatially uncorrelated noise has been chosen to represent a wide class of distortions caused by signal-dependent noise which takes place in many modern applications of CCD sensors, in medical, ultrasound and radar imaging. Recent experiments [24] have clearly demonstrated that existing HVS-metrics do not allow characterizing visual quality of images corrupted by different types of signal-dependent noise adequately.

Comfort noise has been added into consideration to take into account a specific feature of human vision that it practically does not matter for it what realization of the noise takes place for a given image. Similarly, human vision is less sensible to changes in regions with texture. A simplified example of comfort noise is presented in Figures 1 and 2.

Lossy compression of noisy images is one more type of distortions important for practice. Really, original color images acquired by digital cameras in bad illumination conditions as well as video frames are noisy [25, 26]. After lossy compression, additional distortions are introduced. Thus, one needs to assess visual quality in conditions of two types of distortions with their aggregate effect (similar tasks arise in non-reference quality metric design where, e.g., blur and blocking artifacts are present simultaneously). More in detail, additive white Gaussian noise with variance σ^2 has been added and then lossy compression by the DCT-based coder ADCT with the quantization step 1.73σ has been performed.

Finally, sparse sampling and reconstruction (compressive sensing) of images has become a hot topic of research in recent years [27]. Meanwhile, HVS-metrics are practically not exploited for characterizing visual quality of reconstructed images although urgent need in this is obvious. More in detail, the method [28] of compressive sensing image reconstruction has been used by us in generating distorted images.

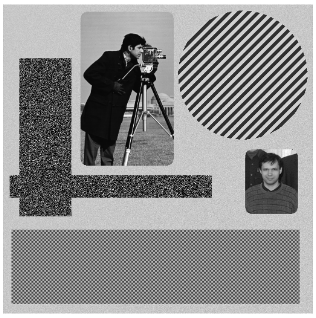
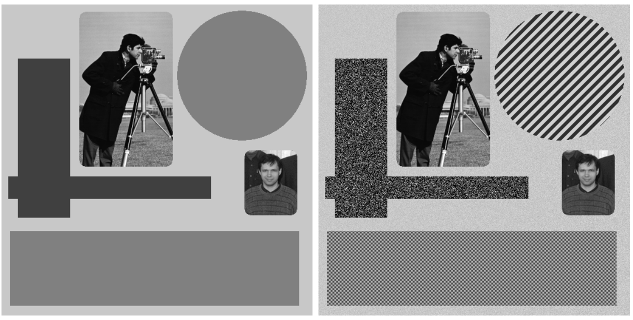


Fig. 1. Reference image



a b

Fig. 2. Distorted versions of the image in Fig. 1 where the image in a) has PSNR=15.4 dB and the image in b) has PSNR=9.9 dB with respect to the reference image.

Experiments with the database TID2013 have been carried out in the same manner as for TID2008. Each image has been subjected to nine comparisons similarly to the way Swiss system is used in chess competitions with a large number of participants. This means that a given image is at the beginning compared to any other one that corresponds to the same reference image. But later only the images with similar numbers of already got points compete. Since the total number of competing images is now equal to 120 (5 levels for 24 types of distortions), each experiment lasted longer than for TID2008. However, the time spent on one experiment never exceeded 40 minutes and was 15 minutes on the average.

Totally, 985 experiments have been performed in five countries (Ukraine, Finland, France, USA, and Italy). 14 abnormal experiments have been then rejected. A specific feature of experiments conducted is that all experiments in Ukraine (602 experiments) were carried out in laboratory conditions under control using recommendations of ITU-R BT.500-13. All experiments in France and significant part of experiments in Italy and in Finland (totally, 201) were performed via Internet.

4. PRELIMINARY RESULTS

Thus, we have obtained MOS for 971 experiments. We have determined Spearman and Kendall ROCC values for a limited number of metrics (standard deviations of these values are about 0.0002 and 0.001, respectively). This list includes the metric FSIM [7], both component-wise and color versions (the latter is denoted as FSIMc), MSSIM [29], NQM [30], SSIM [31], VIFP [32], VSNR [33], and WSNR [34], all calculated for intensity component. All aforementioned metrics (except FSIM) have been computed using the software [35]. We have also calculated ROCCs for PSNR-HVS [36] and PSNR-HVS-M [37] computed for color image intensity. The ROCC values have been also determined for the conventional metric PSNR (computed for intensity using [35]), and the metrics PSNR-HA and PSNR-HMA [9]. The latter two metrics are able to take into account different sensitivity of HVS to distortions in different color components. Besides, we have analyzed the metric PSNRc which is the version of PSNR adapted to color images in the same manner as PSNR-HA and PSNR-HMA [9]. Thus, four metrics are specially intended on accounting for color distortions (they are marked by + in the second column of Table 1).

The obtained results for all 24 types of distortions and for the subset that includes 7 newly introduced types of distortions are presented in Table 1. The three best results are marked by Bold. Spearman ROCC values are larger than corresponding Kendall ROCC values as it usually happens [7, 9]. However, conclusions that can be drawn from analysis of these ROCCs are in good agreement.

The most important observation is that even the largest values of Spearman ROCC are considerably smaller than the largest values of Spearman ROCC attained for TID2008 (see Section 2). For example, Spearman ROCC for TID2008 is equal to 0.884 for FSIMc and 0.880 for FSIM [7]. For TID2013 the corresponding values are considerably less. The same holds for other HVS-metrics as MSSIM, PSNR-HVS, PSNR-HVS-M, etc. There are several HVS-metrics for which Spearman ROCC is less than Spearman ROCC for conventional PSNR calculated component-wise. This means that the database TID2013 seems harder for HVS-metrics pretending to be universal. This conclusion is also confirmed by the fact that Spearman and Kendall ROCC values for the subset of new distortions are smaller than the corresponding values for all types of distortions.

There are also two main conclusions drawn from obtained data analysis that clearly show, at least, two ways to follow in order to improve metrics performance. First, a reliable metric should be able to take into account color information (distortions). This is confirmed by the facts that FSIMc produces better results than FSIM, PSNR-HAc is better than PSNR-HA (see data in Table 1), etc. We expect this to hold for other color HVS-metrics. Second, a good metric should pay more attention to image heterogeneities (edges). This is confirmed by good results produced by both versions of FSIM [8] for both TID2008 and TID2013; similar conclusions are given in [6] and some other papers.

5. CONCLUSIONS

The paper presents a novel database TID2013 that further advances the popular database TID2008 by including seven new types and one more level of distortions. Motivations for making these modifications are presented. The introduced types of distortions and the ways of generation of corresponding images are briefly described. Methodology of carrying out experiments is also revisited. Preliminary results of experiments are presented. These results demonstrate that the created database is quite "hard" for many HVS-metrics in the sense that quite low values of ROCCs between MOS and the analyzed metrics have been obtained. Some reasons for this are given and two possible ways to improve metrics' performance in future are mentioned.

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Table 1. Spearman and Kendall ROCC for MOS and image quality metrics

Metric Analyzed	Color or not	ROCC for all images in the database		ROCC for new subset	
		Spearman	Kendall	Spearman	Kendall
FSIM		0.8007	0.6300	0.6494	0.5236
FSIMc	+	**0.8510**	**0.6669**	**0.7878**	**0.6120**
MSSIM		0.7872	0.6079	0.6314	0.4952
NQM		0.6349	0.4662	0.6258	0.4831
PSNR		0.6395	0.4700	0.6190	0.4728
PSNRc	+	0.6869	0.4958	**0.7772**	**0.5761**
PSNR-HA	+	**0.8187**	**0.6433**	0.7008	0.5416
PSVR-HMA	+	**0.8128**	**0.6316**	**0.7382**	**0.5723**
PSNR-HVS		0.6536	0.5077	0.6471	0.5169
PSNR-HVS-M		0.6246	0.4818	0.6474	0.5179
SSIM		0.6370	0.4636	0.5801	0.4226
VIFP		0.6084	0.4567	0.5921	0.4512
VSNR		0.6809	0.5077	0.5888	0.4374
WSNR		0.5796	0.4463	0.6471	0.5150

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