Detail Diversity Analysis of Novel Visual Database for Digital Image Evaluation

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Abstract: The evaluation of the visual quality of digital images is most commonly performed with various objective and subjective quality assessment methods. To calculate and analyse these methods, usually one of predefined image databases, e.g. TID2008 or TID2013, is used to compare an unmanipulated image with a manipulated one. When comparing quality assessment parameters to the communication value of images, a different, hi-resolution and more detail-oriented image database is required; therefore, a novel database for the evaluation of digital images was developed. Using detail coverage and color difference calculations, the research team designed a series of 30 color images with 28 manipulations that can be successfully used for determining the correlations among various quality assessment parameters, metrics and the communication value (ability to communicate) of digital images. The parameters that were used to manipulate images include sharpness, contrast, noise, compression, resizing and lightness (all were chosen based on real-life photography usage). Using RMSE (root mean square error), PSNR (peak signal to noise ratio) and SSIM index (structural similarity index) assessment methods, the influence of image details on quality parameters was calculated. The calculations demonstrate the importance of each parameter and its influence on the image visual quality. The results show a new way of understanding quality parameters and predicting which quality parameter is more important when the image is more or less complex. Complexity as a mathematical value is closely correlated to the content of an image. Hence, understanding the results of this research can help photographers and editors choose a more suitable digital image for publication. The benefits are not only theoretical, but can be applied instantly in real-life use.

Keywords: photography; image quality assessment; digital image evaluation; image quality parameters; RMSE; PSNR; SSIM; novel image database; visual database

1 Introduction

Images are nowadays the main source of information, as we first observe the image, and then decide if we are going to read the news or not. As a consequence, a large number of images has to be observed, analyzed and tested to decide, which is the best to use. The speed of the so-called image information is constantly on the increase, as more and more images or photographs, respectively, are being taken each second.

Editors, artists and photographers need more time to assess the large amount of image information. To make the process less complicated and time-consuming, the idea of quality assessment was created to determine which images do not apply to the basic quality parameters set by photographers and researchers.

The evaluation of digital images is most commonly performed by different objective and subjective quality assessment methods [1–3] The objective methods used in this research were *RMSE* (root mean square error), *PSNR* (peak signal to noise ratio) and *SSIM* index (structural similarity index). [4]

The *RMSE* (root mean square error) of predicted values, $\hat{y}_i$, for time, i, of a regression dependent variable, y_i, is computed for n different predictions as the square root of the mean of the squares of deviations as shown in Eq. (1).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

The PSNR (peak signal to noise ratio) of predicted values, $\hat{y}_i$, for time, i, of a regression dependent variable, y_i, is calculated for n different predictions. MAX_I is the maximum possible pixel value of the image and MSE stands for Mean Square Error, as used in Eq. (2).

$$PSNR = 10 \cdot log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 10 \cdot log_{10}\left(\frac{MAX_I^2}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}\right) \tag{2}$$

The SSIM index (structural similarity index) is calculated on various windows of an image. Eq. (3) shows the measure between two windows x and y of common size $N \times N$, where μ_x is the average of x, μ_y, is the average of y, σ_x^2, is the variance of x, σ_y^2, the variance of y, σ_{xy} is the covariance of x and y, $c_1 = (k_1 L)^2$, $c_2 = (k_2 L)^2$ are two variables to stabilize the division with the weak denominator, and L the dynamic range of pixel-values, $k_1 = 0.01$ and $k_1 = 0.03$ by default.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{3}$$

To develop and research these methods, one of predefined image databases, e.g. *TID2008* [5], is usually used. When comparing quality assessment parameters to the communication value of images, a different, more detail-oriented image database is required.

The image and video databases used in the quality assessment by Winkler [6] indicate that there are more than a dozen databases available in the public domain that are relevant to quality assessment, and very different research has been conducted with such a procedure. [7–12] A comparison of databases that are publicly available, using the same criterion can be used for testing quality assessment algorithms. The advantages and disadvantages of all tested quality metrics [12] also depend on the viewing conditions, as some researchers believe that controlled lab environment experimental conditions are essential [13], whereas others prefer naturally variable viewing conditions that users experience in their daily life [14], to collect realistic data.

With the overflow of visual information, people are exposed to photographs and images all the time, and as the research indicates, people are good at remembering pictures. [15] SUN dataset [16, 17] images were used in this research to determine the recall of images [18], which is important for advertising, designers and photographers.

In MIT, an algorithm [19] was created to predict the recall of photographs, how memorable or forgettable an image is, to be able to store the information people will most likely remember or forget. This research will help develop better communication systems, teaching resources, social media, as well as advertising and personal health assistant applications to help remember information. There are also researches being conducted on the image quality perception of different devices. [20]

This article focuses on a novel database for the evaluation of digital images that was developed for the purpose of objective evaluation of various image quality parameters. Using detail coverage (percentage of images that is covered with details) and color difference calculations, the research team introduced a series of 30 color images (Figure 1) that can be successfully used for determining the correlations between different quality assessment parameters, metrics and communication values (ability to communicate or successfully transfer message from transmitter to receiver) of digital images. [21] The images in the novel visual database are by about 34% more diverse and also cover a bigger color gamut than the images most commonly used in the Tempere Image Databases *TID2008* and *TID2013*, which contain 25 images distorted at five different levels with 24 types of distortions. [22, 23] The size of images is in both cases 512 × 384 pixels, mainly used for objective visual quality assessment.

Figure 1
All 30 images included in novel image database

2 Experiment

The aim of the experiment was to determine how and which image quality assessment parameters have the greatest influence on image quality.

2.1 Introducing Novel Image Database

First, a novel visual image database of 30 images was introduced. [24] The research team analyzed a new and improved image database of 30 images to investigate the area of image analysis from the photographer's point of view, not merely the mathematical or statistical perspective. *TID2008* and *TID2013* have been used in most research in this field until now; however, when measured and determined, these databases do not have enough detail and color diversity. Furthermore, the images in these databases do not have resolution that would be high enough (512 × 384 pixels) for further subjective testing (a novel visual database has 1920 × 1440 pixels). Considering all of the above, the team is determined that a novel visual image database offers a better foundation for the research.

Detail diversity is one of the most important factors when it comes to the communication value evaluation. Different approaches of image evaluation have been carried out [25, 26], however, for our purpose, detail diversity evaluation was the most suitable. Image diversity is an attribute that is also important for the content-based image retrieval [27, 28]. A comparison between *TID2008* and the novel image database can be observed in Figure 2. From the average pixel value for each image, the research team calculated that the new visual image database is by 34% more diverse regarding the details. Details were visualized with ImageJ: each first image was converted to an 8-bit greyscale image and then the Threshold with 0–75 setting was applied. Counting the white pixels gave us the detail diversity of each image. The average pixel values ranged from 56 for the least detailed image to 253 for the most detailed image (Table 1). For comparison, the values for *TID2008* spread from 116–227.

Figure 2
Visualization of details in images included in TID2008 (left) and novel image database (right)

Table 1
Average monochrome pixel value for each image in novel image database.
Higher number means more details.

Image number	Average monochrome pixel value	Image number	Average monochrome pixel value	Image number	Average monochrome pixel value
1	56,348	11	184,742	21	237,098
2	90,111	12	185,917	22	237,98
3	105,057	13	192,963	23	243,943
4	118,425	14	200,337	24	245,169
5	132,95	15	206,845	25	248,511
6	138,244	16	215,736	26	248,519
7	154,052	17	223,593	27	248,528
8	162,232	18	231,808	28	250,496
9	172,681	19	235,347	29	251,694
10	175,431	20	235,747	30	252,866

2.2 Selecting Image Quality Assessment Parameters

The parameters that have the most influence on the image communication value were specified and for each, a mathematical manipulation to simulate the real effect was selected. In this research, the team used the following:

- sharpness (Gaussian blur for decreasing and unsharp mask for increasing – unsharp mask was included as it is commonly used method by photographers: method cannot directly correct sharpness errors caused by the lens or processing, but it includes calculations that give us sharper results),
- contrast (lower contrast for decreasing and higher contrast for increasing),
- noise (poisson, salt & pepper and speckle noise – all for increasing),
- compression (jpeg and jpeg2000 compression levels for increasing),
- size (resizing),
- lightness (lower lightness for decreasing and higher lightness for increasing).

The parameters were chosen based on the direct influence of the digital camera and digital workflow on the digital image visual quality (Table 2).

Table 2
Influence of digital camera on visual quality

	sharpness	contrast	noise	compression	size	lightness
lens	✓	✓	–	–	–	✓
shutter	–	–	–	–	–	✓
sensor	–	✓	✓	–	–	✓
processing	✓	✓	✓	✓	✓	✓

2.2.1 Sharpness

The manipulation of sharpness was conducted in two ways – by decreasing and increasing:

- Decreasing was performed with Gaussian blur in three steps, using Matlab, function “fspecial”, parameter “Gaussian”, radius 5, 10 and 15, and sigma 5, 10 and 15.
- For increasing, sharpness unsharp masking was used in three steps, using Matlab, function “fspecial”, parameter “unsharp”, and radius 0.2, 0.5 and 1.0.

For each of the 30 images, three manipulations with decreased and three with increased sharpness were obtained.

2.2.2 Contrast

The manipulation of contrast was done in two ways – by decreasing and increasing:

- Decreasing was conducted using Matlab, function "imadjust", where the matrix parameter was manipulated with values 0.1, 0.2 and 0.3.
- Increasing was conducted using Matlab, function "imadjust", where the matrix parameter b was manipulated with values 0.4, 0.6 and 0.8.

For each of the 30 images, three manipulations with decreased and three with increased contrast were obtained.

2.2.3 Noise

The manipulation of noise was carried out in three different ways, all increasing noise in the image:

- Salt & pepper noise was applied in three steps using Matlab, function "imnoise", parameter "salt & pepper", and values 0.05, 0.10 and 0.20.
- Speckle noise was applied in three steps using Matlab, function "imnoise", parameter "speckle", and values 0.05, 0.10 and 0.20.
- Poisson noise was applied using Matlab, function "imnoise" and parameter "poisson".

For each of the 30 images, seven noise manipulations were obtained.

2.2.4 Compression

The manipulation of compression was performed in two ways, in both by increasing compression:

- Increasing compression in three steps using JPEG standard, Matlab, function "imwrite", parameter "Quality", values 50, 30 and 10.
- Increasing compression in three steps using JPEG2000 standard, Matlab, function "imwrite", parameter "QualityLayers", values 20, 10 and 5.

For each of the 30 images, we got six manipulations with increased compression.

2.2.5 Size

The manipulation of size was conducted first by decreasing the image size and then by increasing it back to the original size in three steps. Matlab, function "imresize", and values 0.90, 0.75 and 0.50 were used.

For each of the 30 images, we obtained three resized manipulations.

2.2.6 Lightness

The manipulation of lightness was done in two ways – by decreasing and increasing:

- Decreasing was conducted using Matlab, function “imadjust”, and by manipulating matrix parameter d with values 0.4, 0.6 and 0.8.
- Increasing was conducted using Matlab, function “imadjust”, and by manipulating matrix parameter c with values 0.2, 0.4 and 0.6.

For each of the 30 images, we got three manipulations with decreased contrast and three with increased contrast.

2.3 Database Structure

Applying each of the described parameters and manipulating saturation (which is not presented in this paper, as the team was only researching the complexity of images) in one to six levels in each image, the team developed 1140 different images, altogether called a novel image database. The image manipulation was conducted in Matlab R2014a and all the images were saved in the BMP file format with 1920 × 1440 pixel resolution, suitable for a subjective testing in further research.

2.4 Calculating Objective Image Quality

The next stage was to calculate the objective image quality, using different objective quality assessment methods, e.g. RMSE (root mean square error), PSNR (peak signal to noise ratio) and SSIM index (structural similarity index). These are the most commonly used methods for the visual quality analysis of monochrome images – we were mostly interested in detail diversity, thus, color information was not relevant for this research. The calculations were carried out by comparing the original (reference) or unmanipulated image with the manipulated one (for each of the 30 images in the database, 34 calculations were performed with each method).

3 Results and Discussion

Preliminary research showed significant advantages of the new novel visual image database, which can be used for objective and subjective testing. This database covers a significantly wider color range (34%) and also contains higher resolution images than *TID2008* and *TID2013*. It represents the possibility of testing different aspects of image quality and communication value, using the same image database during the whole process.

The selected images are based on human perception and experiences, and differ in the characteristics such as motive variation and detail coverage. A subjective testing provides accurate results now and hopefully also in the future. The results are practically oriented and the discussion also presents some direct instructions for photographers that are supported with calculations.

3.1 Examples of Image Manipulations

All 30 images in the novel image database were manipulated in different ways. Six examples can be seen in the image number 18, where only the most manipulated samples are presented: sharpness, noise, contrast, JPEG compression and lightness. (Figure 3)

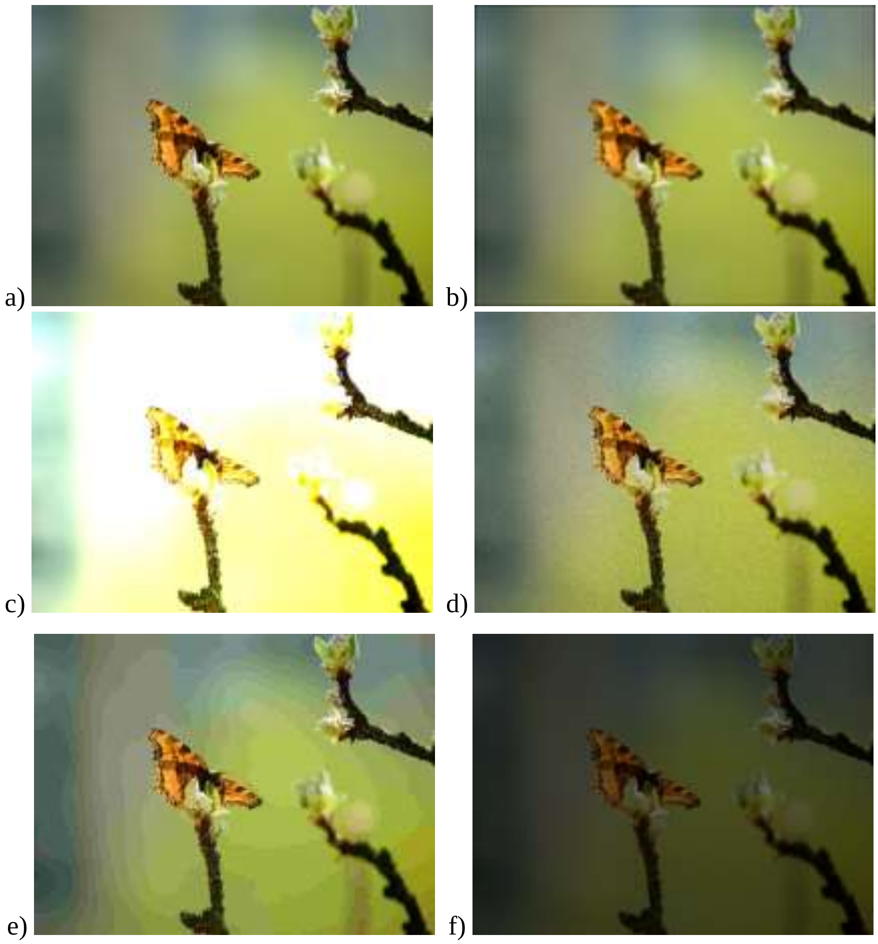

Figure 3
Image 18 from novel image database: a - unmanipulated, b - decreased sharpness, c - highest contrast, d - highest noise, e - highest JPEG compression, f - lowest lightness

3.2 Sharpness

In Figure 4, the relation between SSIM and the average pixel value of images with manipulated sharpness can be observed. A comparison of reference images with manipulated images indicates that a higher level of details in the image has a greater influence on the image quality when manipulating its sharpness (increasing or decreasing). The SSIM index results are spread across the total range, as it was expected. The smaller the details in the image, the greater the influence of blur or unsharp mask on its quality – there are more elements that can be changed according to the original. Therefore, it can be easily concluded that sharpness has a large influence on the image communication value. As a consequence, it is recommended for photographers to use good quality lenses and a short shutter speed.

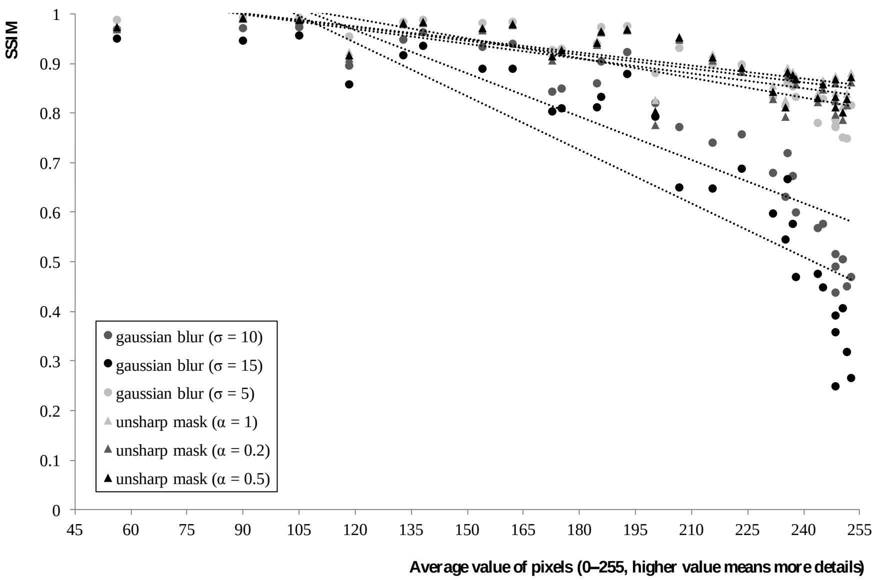

Figure 4

Influence of sharpness manipulation on image quality

3.3 Contrast

The relation between SSIM index and the average pixel value of images, presenting manipulated contrast, is shown in Figure 5, where it is demonstrated that a higher level of details in the image has a greater influence on the image quality when manipulating its contrast. The number of details offers more possibilities for the contrast changes to have a greater effect, which was also expected. The *SSIM* range is not as wide as in sharpness manipulation; thus, it can be concluded that contrast changes have a smaller effect on the image quality than sharpness. Nevertheless, contrast is very important when it comes to image quality. Photographers are very dependent on their equipment and have a very small influence on the contrast itself in the production phase; the contrast should therefore be corrected in the post-production.

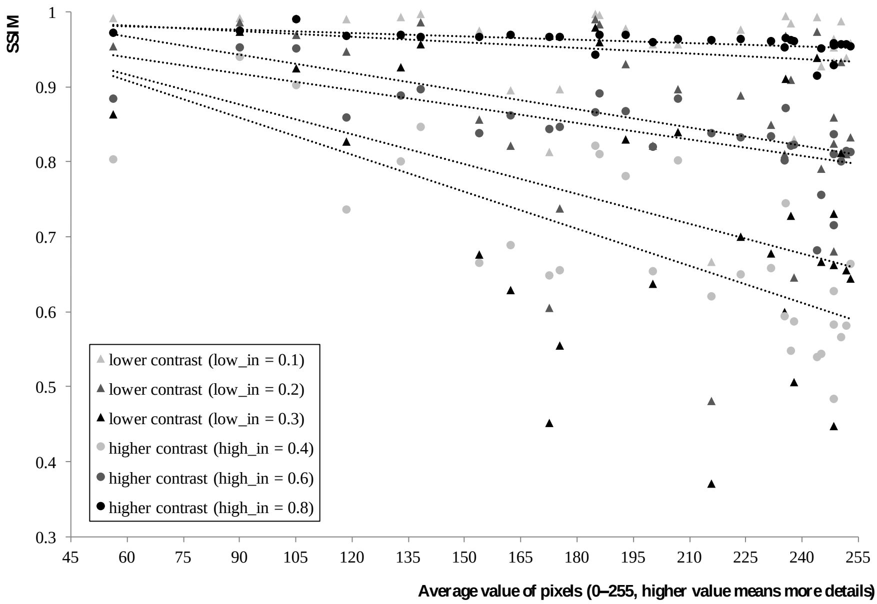

Figure 5

Influence of contrast manipulation on image quality

3.4 Noise

Noise is a common disadvantage of higher ISO sensitivities. The relation between SSIM index and average pixel value of images with manipulated noise is presented in Figure 6. The situation is very different than with sharpness and contrast: it can be seen that a lower level of details in the image has a greater influence on the image quality when manipulating its noise. The reason is that a higher number of details that is constructed out of more different image pixels offers a greater ability to hide noise, whereas noise can be easily seen on flat surfaces with very little pixel differences. To avoid noise, photographers should not use higher ISO sensitivities.

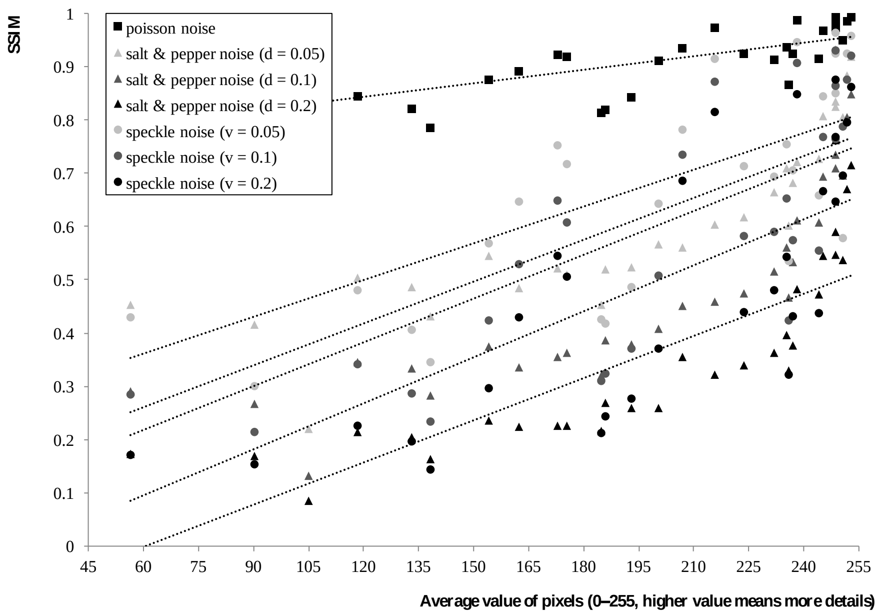

Figure 6
Influence of noise on image quality

3.5 Compression

Regarding compression, the team looked into the JPEG and JPEG2000 compression algorithms. The relation between SSIM index and average pixel value of images with manipulated compression is shown in Figure 7. The team established that the level of details in the image has no significant influence on the image quality when manipulating its compression. That does not mean that compression has no influence on the image quality, it actually has a very high influence. The increase in compression results in a lower image quality, whereas the number of details in the image does not really influence the result. A very low-level of compression is recommended for photographers.

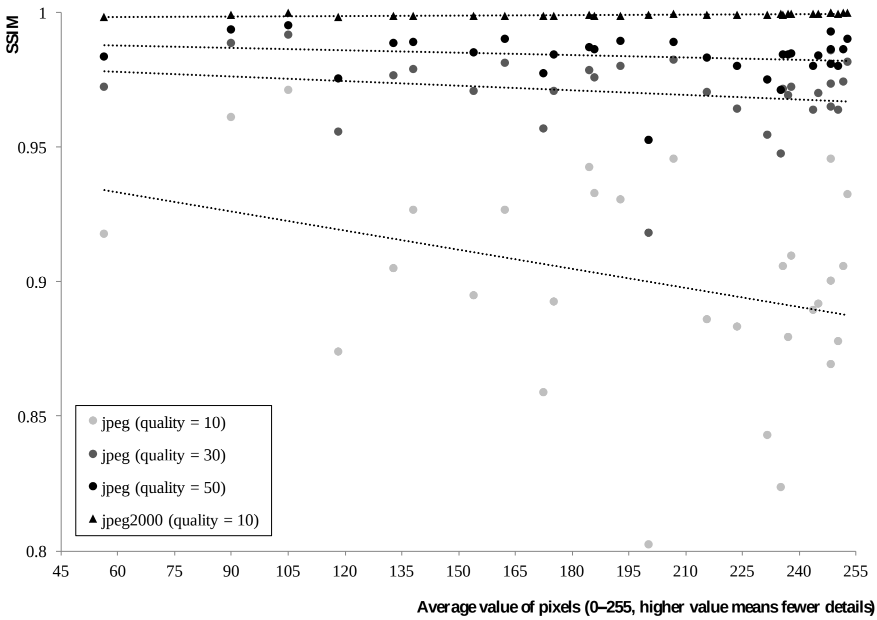

Figure 7

Influence of compression on image quality

3.6 Size

The size manipulation in the images was made by scaling the images down by 10%, 25% and 5%, and then reversed, scaling them back to their original resolution. The image quality drop was expected. The relation between SSIM index and average pixel value of images that have manipulated size is presented in Figure 8. In all cases, even with 10% manipulation, the image quality dropped significantly and a higher level of details in the image, influenced the image quality when manipulating its size. More details lead to more possibilities to losing information and a higher drop in image quality. Scaling up the images is not recommended if high image quality is desired.

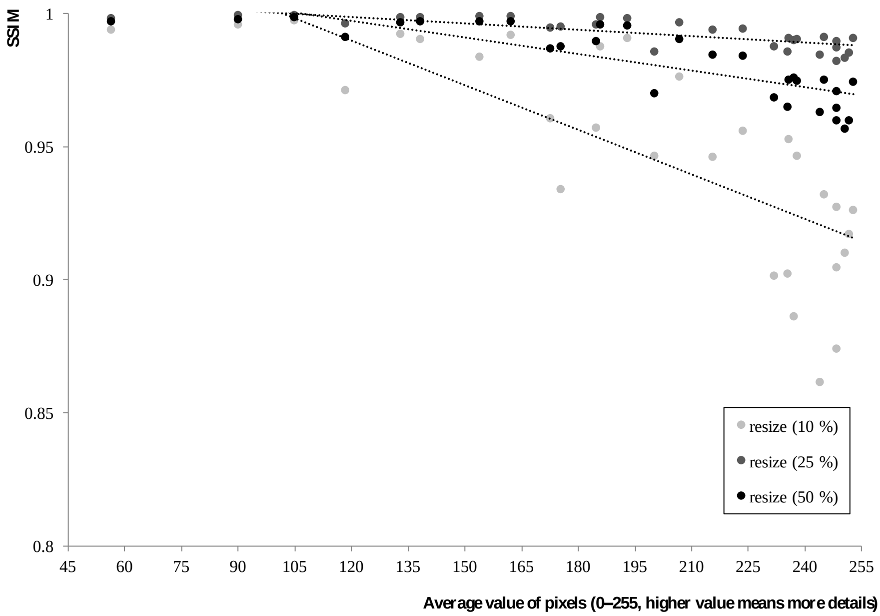

Figure 8
Influence of size manipulation on image quality

3.7 Lightness

There are few photography settings that influence image lightness, e.g. shutter speed, aperture size and ISO sensitivity. In contrast to other cases, a comparison between SSIM index and the level of details has not lead to any noticeable findings. The team therefore compared PSNR to the average image lightness. Figure 9 shows that the image quality drop is higher when lowering brightness on darker images or raising brightness on lighter images. The reason lies in the dynamic range, where the bit depth of the image does not allow the rendering of more details in very dark or very light areas. Photographers should always work with optimal photography settings.

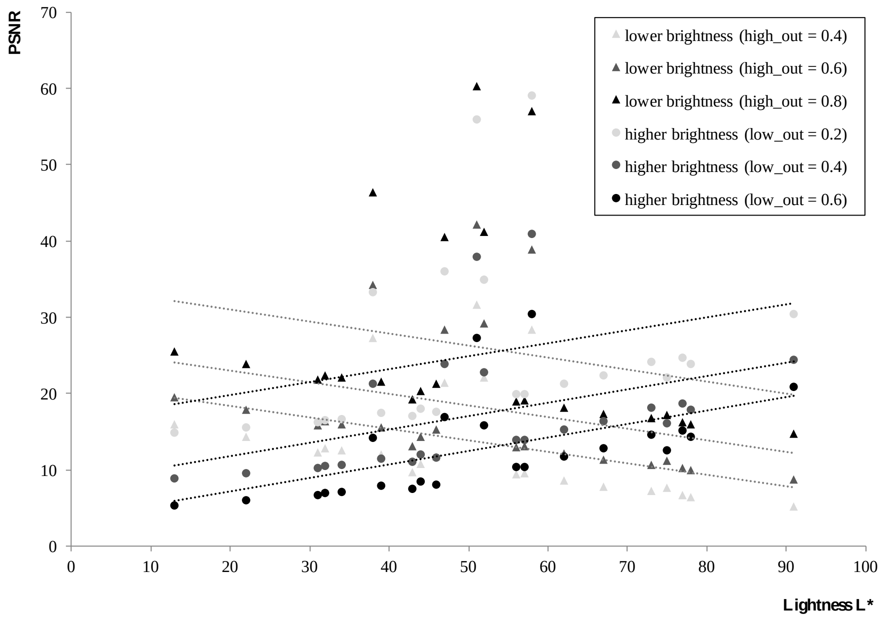

Figure 9
Influence of lightness on image quality:
average image lightness influences image quality when manipulating its brightness

Conclusions

This paper is focused on the presentation of evaluation of different image quality parameters. The influence of image complexity on the image quality parameters has been analysed and the conclusions are as follows:

- sharpness: more details in the image, the greater the influence of sharpness on its quality,
- contrast: more details in the image, the greater the influence of contrast on its quality,
- compression: more details in the image, the greater the influence of compression on its quality,
- size: more details in the image, the greater the influence of resizing on its quality and
- noise: less details in the image, the greater the influence of noise on its quality.

The more complex images are, in most cases more under the influence of the image quality decrease, so working with less complex images can be more flexible. Communication value is preserved when image has less communication elements and has been manipulated in the process. These conclusions are very important not only for researches but also for editors and other communication experts.

This research has also confirmed some of the well-known recommendations for photographers:

- regarding lightness, work in optimal photography settings,
- for increased sharpness, use good quality lenses and short shutter speed,
- to avoid noise, photographers should not use higher ISO sensitivities,
- contrast should be corrected in the post-production,
- scaling up the images is not recommended if high image quality is required; therefore, a very low-level of compression is recommended.

In further research, the novel visual database will be tested on different quality assessment metrics, using subjective testing methods and methods for measuring the image communication value (some methods are still to be developed). Subjective measurements will be performed with observation and eye movement measurement, and the team believes that the results will confirm the present research. The final goal is to have some real objective parameters from which usable results for the communication value prediction could be determined. The exact numbers and a comparison between different quality parameters are important for understanding the real world experience users have when observing images. Knowing that some quality parameters do not have such a substantial influence on the image quality than others can help editors decide what to include into their publications, or which images will have a better communication value. At the end of the research, the novel visual database will be publicly available for other researchers.

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