Sharpness metric for no-reference image visual quality assessment

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ABSTRACT

This paper presents a novel sharpness metric for color images. The proposed metric can be used for no-reference assessment of image visual quality. The metric basically relies on local power of wavelet transform high-frequency coefficients. It also takes into account a possibility of the presence of macrophotography and portrait photography effects in an image where the image part (usually central one) in sharp whilst the remained part (background) is smeared. Such effects usually increase subjective evaluation of image visual quality by humans. The effects are taken into consideration by joint analysis of wavelet coefficients with largest and smallest squared absolute values. Besides, we propose a simple mechanism for blocking artifact accounting (if an image is compressed by JPEG) and compensation of this factor contribution. Finally, the proposed sharpness metric is calculated in color space YCbCr as a weighted sum of sharpness components. Weight optimization has shown that a weight for intensity component Y has to be considerably smaller than weights for color components Cb and Cr. Optimization of weights for all stages of sharpness metric calculation is carried out for specialized database NRTID that contains 500 test images with previously determined MOS (Mean Opinion Score). Spearman rank order correlation coefficient (SROCC) determined for the designed sharpness metric and MOS is used as an optimization criterion. After optimization, it reaches 0.71. This is larger than for other known available no-reference metrics considered at a verification stage.

Keywords: blind quality assessment, visual quality, human vision system, no-reference metric, image analysis

1. INTRODUCTION

No-reference metrics of image visual quality are widely used in many applications of image and video processing[1-3]. One application area is a preliminary assessment of visual quality of images captured by imaging systems. Another possible application where such metrics are of value is data processing in content-based image retrieval (CBIR) and multimedia information storing and transferring systems. Here, visual quality assessment can be exploited for image indexing and sorting.

Although design and testing of no-reference visual quality metrics is a topic of intensive research[1], there are no such no-reference metrics till the moment that can satisfy users in full extent. Recent studies[4] show that Spearman rank correlation factor for known no-reference metrics and image visual quality perception by humans (characterized by MOS) does not exceed 0.6. The main reasons for this are the presence of a large number of different factors that determine quality perception by humans and the problem of taking these factors into account jointly in quality metrics at their design stage. The aforementioned general problem can be decomposed to less complex tasks to be solved. First, each factor has to be correctly evaluated (characterized) and its influence on image quality has to be carefully estimated (predicted). One example is a blind evaluation of noise type and characteristics in a given image[5]. A set of dominating factors has to be determined. Second, design of an integral metric able to incorporate estimated parameters for the considered factors is also a difficult task. The reason is that one needs to jointly process (aggregate) several parameters that have different physical nature. For example, how to aggregate parameters describing such factors as color depth and image size that both influence image quality perception by humans? Third, humans exploit both low and high level features in assessment of image visual quality where the latter ones are difficult to incorporate in any metric.

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There are many factors known to affect assessment of image visual quality by humans:

- Image sharpness;
- Noise level and spatial correlation;
- Blur level;
- Color depth;
- Dynamic range;
- Image size;
- Presence of blocking artifacts and Gibbs effects;
- Macrophotography and portrait photography effects;
- Mean intensity;
- Color temperature;
- Scene composition;
- Vertical symmetry presence;
- Uniformity of information distribution;
- Presence of artificial insertions (signs, letters and words, frames added in graphical editor);
- Image type (e.g., screenshot, plot, animation frame);
- People (face) and/or animal presence;
- Image content that attracts more or less interest.

Value of some factors can be evaluated quite accurately. Examples are color temperature, brightness, dynamic range, noise type and level. However, other factors, such as, e.g., image content (an image can be non-ordinary or amusing) is problematic to evaluate automatically (at least, it seems impossible in the nearest future). Meanwhile, such factors can play a key role in some situations. For instance, a photographer has occasionally made a human face out of focus whilst other parts of a photo have sharp details. Then, any sharpness indicator characterizes this image as good enough whilst a human might be disappointed by its visual quality. This example deals with the fundamental problem in image search by similarity[5] and analysis by humans. People exploit higher order semantic features in more or less extent but computer tools have to rely mainly on low-level features of a considered image.

To our best knowledge, there are no publications where a design of no-reference visual quality metrics is carried out taking into account all or, at least, most of factors listed above. There are numerous papers devoted to evaluation of particular factors. Probably, the blocking artifacts in JPEG compressed images are studied most intensively (see the papers[6-8] and references therein). The papers[9,10] and some others consider measures of image blur. Sharpness measures are studied in publications[11-15]. Meanwhile, there are quite many recent publications[9,16,17] where researchers have (with certain success) tried to take into account two or more factors and shown expedience of this for improving quality metric performance.

One more drawback of many existing no-reference metrics is that they have not been intensively and extensively verified. Note that many proposed metrics are heuristic and not based on thorough mathematical models (this is partly explained by absence of adequate models). Then, metric's performance has to be analyzed in practical experiments carried out with careful planning. However, people often use existing databases for proposed metric verification without taking into account that these databases have been, in fact, designed for other purpose. For example, the metric[9] has been verified for the database LIVE[18] originally created and intended for verification of full-reference metrics of image visual quality. Because of this, the presented impressive results of metric efficiency (Spearman rank order correlation coefficient is equal to 0.936) are, most probably, overestimated. A possible reason is that the set of distorted images used in LIVE is not in good agreement with properties of real-life images met in practice (this set is too refined, e.g., blur is artificially added by low-pass linear filtering).

Necessity to have databases for verification of no-reference metrics becomes obvious nowadays. Without having inverse impact from metric verification using such databases, it is difficult to objectively compare metrics between each other, to optimize metric parameters and to find ways of metric improvement. The paper[4] deals with creation of such database and its use for verification of several metrics. This database contains 500 images and MOS values for each of them. It is demonstrated[4] that for none of the considered metrics SROCC does not exceed 0.45 (in particular, SROCC for the metric[9] with MOS is equal to 0.315 which is quite low). On one hand, the presented data demonstrate problems and actuality of a no-reference visual quality metric design. On the other hand, they show that the database NRTID[4] is quite complex and it allows retrieving drawbacks of existing metrics.

This paper proposes a novel sharpness metric and estimates importance of this factor in image perception by humans. Recall that we would like to have a sharpness metric that increases with better visual quality as this property holds for most known no-reference and full-reference metrics. Besides, it is desirable to have a metric that can be calculated quickly enough.

The paper is organized as follows. Section 2 describes block-diagram for metric calculation. Section 3 gives more details of metric calculation for each color component. Macrophotography effects are considered in Section 4, one way to take it into account is presented. In turn, Section 5 describes how blocking artifacts and their contribution into image sharpness can be taken into account. A way to metric calculation for color images is presented in Section 6. Finally, Section 7 deals with a metric optimization and verification using the image database NRTID.

2. BASIC IDEA OF THE PROPOSED SHARPNESS METRIC

The main contribution in image sharpness assessment by humans is done by high-frequency components. Just because of this, amplification of high frequency components is performed in image reconstruction (deblurring). Thus, it seems reasonable to separate image low-pass and high-pass information using some orthogonal transform and then analyze only these high-frequency components. Different orthogonal transforms can be applied for this purpose as, e.g., discrete cosine transform (DCT)[19] or discrete wavelet transform (DWT)[20]. Below we use the latter transform because of the following two reasons. First, DWT is just based on high-pass and low-pass decomposition of data. Second, DWT (its realization used below) requires less computations and is very fast.

For our purpose, we exploited 2D DWT based on 9/7 wavelet (from JPEG2000 standard[21]) with two decomposition levels. The upper left quadrant relates to the low spatial frequencies and we will not consider data in it. We will analyze data in other three quadrants that basically relate to high frequencies (more exactly, LH, HL and HH quadrants). For each four pixels of original image, there are three high frequency coefficients, one in each of LH, HL and HH quadrants. Our algorithm of sharpness metric calculation is based on calculation of sums of these three high frequency coefficients as initial stage and their correction and processing at next stages (see Section 3). These serve as local estimates of image sharpness. They form a map of sharpness distribution that allows taking into account macro- and portrait photography effects (see Section 4).

Such a map of high-frequency DWT coefficients' power has a specific appearance for images compressed by JPEG with rather high compression ratio (there is a grid corresponding to block margins). Blocking artifacts have no relation to image sharpness but they can influence the metric value. Thus, its negative influence has to be estimated (Section 5 presents a way to do this) and the sharpness metric is corrected, respectively.

Fig. 1 presents generalized block-diagram of the proposed algorithm for sharpness metric calculation for a given component of a color image or a grayscale image. Details concerning each block of this block-diagram and other stages are presented in the next sections.

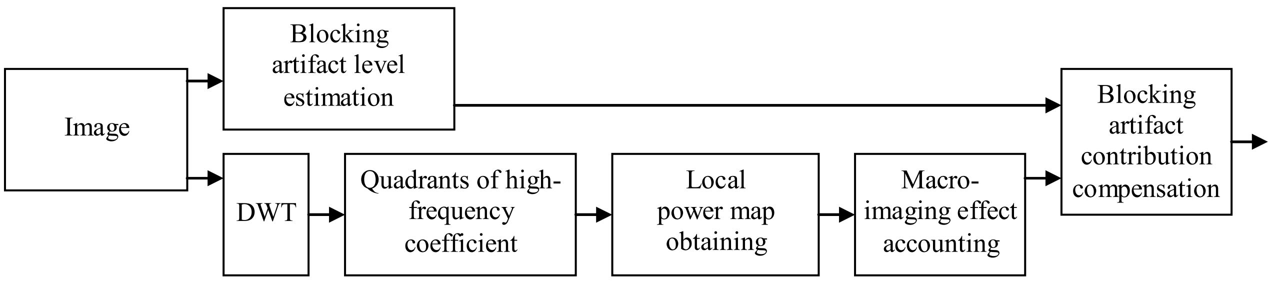

Fig. 1. Block-diagram of sharpness metric calculation for a given color component

3. LOCAL POWER MAP CONSTRUCTION FOR A GIVEN COLOR COMPONENT

Let one has a color image of size M x N pixels. If it is originally in RGB color space, let us convert it to YCbCr color space. A procedure described below is carried out separately for each components Y, Cb, and Cr. If a given image is a grayscale, then one has only intensity component Y which is used to form a local power map forming whilst other (color) components are absent. Each component is a subject to 2D DWT CDF 9/7 used in JPEG2000 standard compression. Low-pass and high-pass filter coefficients are presented in Table 1. Index 0 in this Table corresponds to the central sample in 1D data array for which output value is calculated. These coefficients are presented below since they are not unique.

Table 1. Coefficients of the used wavelet transform

Index	-4	-3	-2	-1	0	1	2	3	4
Low-frequency component	0.02675	-0.0169	-0.0782	0.26686	0.60295	0.26686	-0.0782	-0.0169	0.02675
High-frequency component	0	0.09127	-0.0575	-0.5913	1.11509	-0.5913	-0.0575	0.09127	0

2D DWT is carried out in the following manner. 1D DWT is performed for each row, then the obtained 2D matrix of DWT coefficients is transposed and 1D DWT is carried out one more time. Low-pass filter output is calculated for each even array element. Similarly, high-pass filter output is obtained for each odd array element at 1D processing stage. Then, the total number of low-pass and high-pass coefficients is the same as the number of pixels in an original image.

Let us consider only high-frequency components (quadrants) of the obtained 2D DWT and denote wavelet coefficients in them as LH, HL and HH (the corresponding data arrays have size M' = M/2 and N' = N/2). The local power map has the same size and its elements can be calculated as $E_{ij} = (LH_{ij}^2+HL_{ij}^2+HH_{ij}^2)/3$.

Fig. 2 presents the test image # 22 from the database TID2008 [22] and zoomed visualized local power map obtained for Y component of this noise/distortion-free image. As it is seen, the map clearly indicates positions of sharp edges and high contrast details in this image.

Fig. 2. An example of the image and local power map obtained for its Y component

4. ACOUNTING FOR MACROPHOTOGRAPHY AND PORTRAIT PHOTOGRAPHY EFFECTS

It might seem that the obtained map $\{E_{ij}\}$ already contains necessary information to calculate an integral sharpness metric as, e.g., mean value of the map. Really, for an image having more details and better contrasts, a value of such metric is larger. However, there is a class of images and a set of factors that can deteriorate such metrics. We have already mentioned images captured in macro (acquired from small distances with object magnification) and portrait photography modes. For both modes, it is typical that a part of an image is in focus whilst other part is blurred. It is considered that such a combination of sharpness and blur provides “volume” to captured images while images that have good sharpness in all parts seem “flat”. Fig. 3 presents and example of such an image (# 23 from the database TID2008) captured in portrait photography mode, the zoomed local power map for its component Y is represented as well.

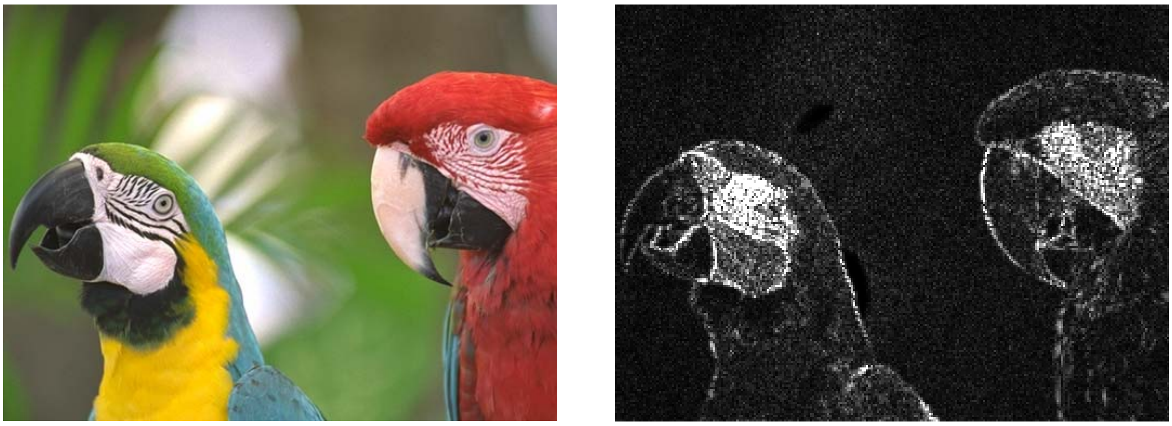

Fig. 3. Portrait photography mode image and zoomed local power map for its Y component (lighter pixels correspond to larger values of E_{ij})

Map analysis shows that rather small values of E_{ij} are observed for many pixels of the map. Then, sharpness metric calculated as the map mean will produce quite small value indicating middle or low visual quality of the image. Meanwhile, we would like to have a rather large value of our sharpness metric for such images.

One more factor influencing image perception by humans is noise. Obviously, people prefer noise-free images (compare images presented in Figures 3 and 4 (left)). The image in Fig. 4 is corrupted by additive white Gaussian noise with variance equal to 525. The local power map for the component Y is given in Fig. 4 (right).

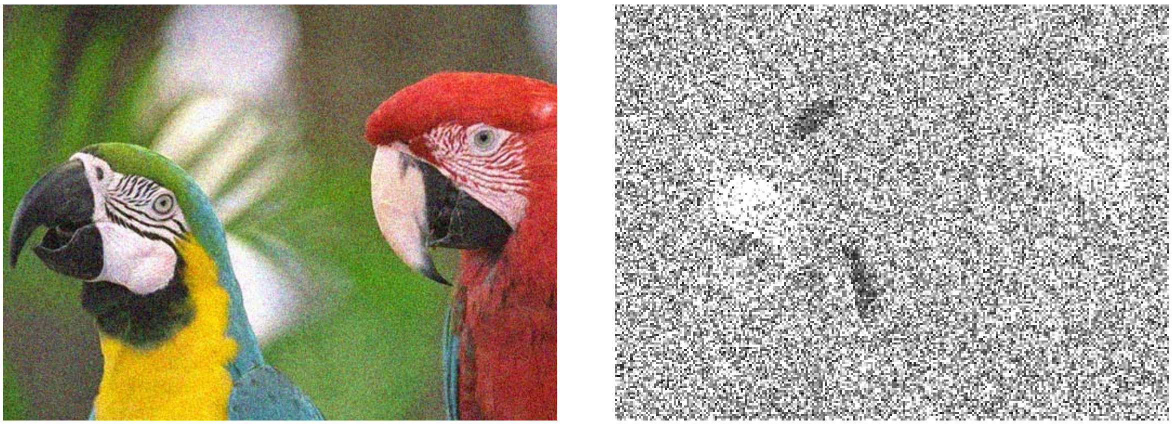

Fig. 4. Illustration of noise influence on image visual quality and local power map

Its analysis shows that noise presence increases local values of the map. Then, if a sharpness metric relies on the map mean, this can lead to confusion (noisy image has a larger metric value whilst a human surely prefers the image without visible noise). This means that humans analyze both image fragments with high activity (edge/detail neighborhoods) and homogeneous image regions to get aggregate opinion.

These observations have led us to an idea that not map mean but some estimate of map scale can serve better for characterization of image sharpness. Based on this idea, we propose the following procedure for local power map modification and sharpness metric calculation. First, the obtained map $\{E_{ij}\}$ is processed by the 5x5 mean filter to obtain the smoothed version $\{EF_{ij}\}$. These smoothed versions are presented in Fig. 5 for the maps given above in Figures 3 and 4 (right). It is seen that smoothing makes maps more “homogeneous” with decreasing variations of local power estimates.

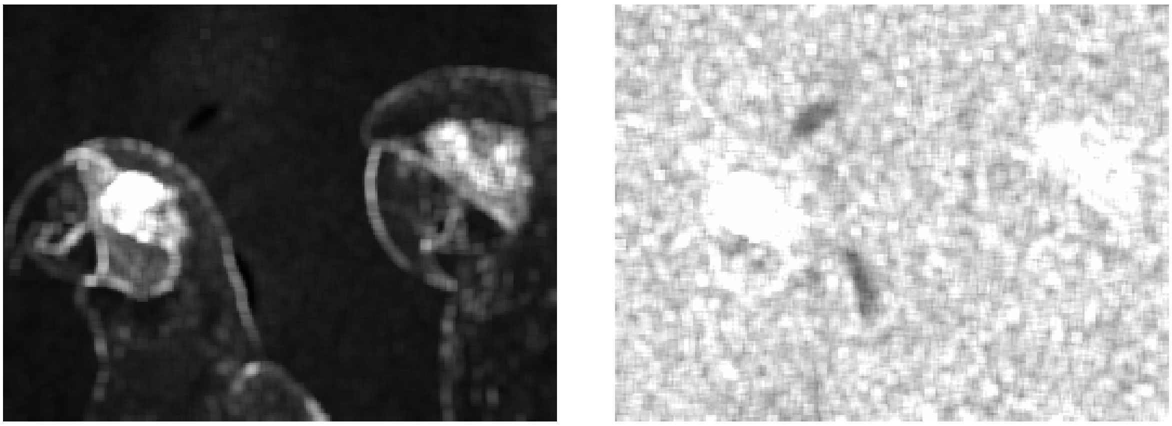

Fig. 5. Smoothed maps $\{EF_{ij}\}$ for the maps $\{E_{ij}\}$ in Figures 3 and 4 (right), respectively

Let us then transform the 2D data array $\{EF_{ij}\}$ into 1D data array D of size M' x N' = MN/4 by sorting in ascending order. Then we propose to calculate initial modification of sharpness metric as

$$S = \frac{1}{10^6}\left(\sum_{l=M'N'-t}^{M'N'} D_l - K\sum_{l=1}^{k} D_l \right), \tag{1}$$

where K denotes weighting factor, k defines the number of the summed-up smallest values of D, t is the number of the summed-up largest values, M' and N' define the local power map size, $1/10^6$ is the normalizing factor that allows convenient representation of the obtained results. It is worth stressing that, in fact, full sorting of the data array D is not needed for calculating the metric S in (1) and this can accelerate processing.

Note that $\sum_{l=1}^{k} D_l$ characterizes noise variance[23]. This means that by (1) we actually compensate the noise influence if the noise is present. At the same time, the structure of expression (1) is similar to different robust scale estimators based on order statistics [24].

Using the test image database NRTID[17], the following values of factors (parameters) for the expression (1) have been obtained: K=0.1263, k=0.05M'N', t=0.95M'N' (methodology of parameter optimization for our sharpness metric is described in Section 7).

Concluding this Section, let us give the values of S for the map in Fig. 3 (S = 3.468) and in Fig, 4 (S = -0.967). As it is seen, the desired property of the metric under design is reached. The noisy image has less sharpness and now the metric (1) clearly indicates this. Table 2 presents S values for Y component of noisy images (original noise-free image is given in Fig. 3, left) with different variances of artificially added white Gaussian noise. It is seen that if noise variance increases, the values of sharpness metric decrease as desired (these values can be even negative for the cases of very intensive noise).

Table 2. Illustration of S reduction with noise variance increase

σ^2	0	64	130	260	525
S	3.468	2.870	2.293	0.9980	-0.9670

Note that expression (1) in no way takes into account an analyze image size. Certainly, it is possible to carry out some normalization. This can be done by using some factors, e.g., 1/(M'N') instead of $\frac{1}{10^6}$ used in (1). However, our previous studies carried out for NRTID[17] have demonstrated that larger size images are, in general, better perceived by observers (numbers of pixels for images in NRTID differ by no more than 2.5 times). Because of this, we have decided to carry out no normalization of the proposed metric taking into account image size. We plan to discuss and study this aspect more in detail in future.

5. ESTIMATION OF JPEG BLOCKING ARTIFACTS AND COMPENSATION OF THEIR CONTRIBUTION

Fig. 6 (left) presents the test image in Fig. 2 (left) compressed by JPEG. In turn, Fig. 6 (right) represents the zoomed map $\{E_{ij}\}$ for this case. Its comparison to the map in Fig. 2 (right) shows that blocking artifacts introduce sufficient distortions increasing the map values near block margins in homogeneous and quasi-homogeneous image regions. S=4.745 for the original image (Fig. 2, left) and S=3.385 for the compressed image (Fig. 6, left) although we expect to have smaller values of sharpness metric for images corrupted by intensive blocking artifacts. Thus, our proposition is to evaluate image blockiness by some parameter and to compensate its contribution to the sharpness metric S.

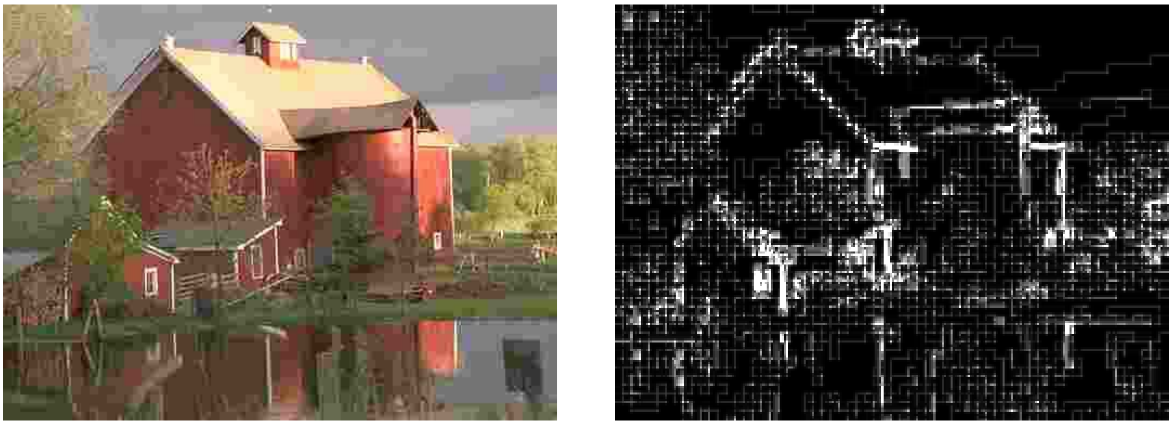

Fig. 6. The image compressed by JPEG with large compression ratio and the visualized map of local power for component Y

Usually, the level of blocking artifacts is evaluated in the neighborhood of block margins. In our case, we propose applying the following simple algorithm. For a considered original image (before carrying out DWT), let us process it by 2x2 scanning window and calculate local variance for each scanning window position. The sums of local variance values that correspond to margins of 8x8 blocks are accumulated in parameter Q_1. The sum of other values of local variances is, in turn, accumulated in parameter Q_2. Then, parameter Q that characterizes contribution of blocking artifacts into image sharpness (integral power of high frequencies) is calculated as

$$Q = \max\left(0, Q_1 - \frac{15}{49} Q_2\right),$$

where the factor 15/49 takes into account the total numbers of terms in the formed sums (Q is close to zero if blocking artifacts are absent in a given image). Having obtained Q, it is possible to evaluate blocking artifact contribution into aggregate sharpness of a considered image by the parameter

$$P = \begin{cases} Q, & Q_1 + Q_2 = 0 \\ Q/(Q_1 + Q_2), & Q_1 + Q_2 > 0 \end{cases}.$$

Finally, after obtaining P, it becomes possible to calculate the next modification of the sharpness metric S^b as

$$S^b = S(1 - P * K_b), \qquad (2)$$

where S^b is the modified sharpness metric that takes into account blocking artifacts, K_b denotes the weight. According to optimization results (see Section 7), we propose to use K_b=2.

For example, the blocking artifact contribution to Y component of the image in Fig. 6 (left) is characterized by P=0.203. Then, substituting this values to (2), one gets $S^b = 4.745\ (1\text{-}2*0.203) \approx 2.82$.

6. METRIC CALCULATION FOR COLOR IMAGES

Recall that an analyzed image has to be represented in YcbCr color space. Then, the metrics S^b are calculated for each component separately according to (2) with obtaining $S^b{}_Y$, $S^b{}_{Cb}$, and $S^b{}_{Cr}$, respectively. The aggregate metric is then calculated as

$$S_{fin} = S^b{}_Y + w_{Cb}\, S^b{}_{Cb} + w_{Cr}\ S^b{}_{Cr}, \tag{3}$$

where the weights w_{Cb} = 50 and w_{Cr} = 10 have been obtained by optimization carried out for the database NRTID (see details in the next Section). Here it is worth mentioning that these values of the weight maximize SROCC between the proposed metric and MOS. The fact that the optimized weights for components Cr and, especially, Cb have occurred to be considerably larger than for the component Y might seem to be a little bit surprising. We explain this by the fact that humans prefer images having larger color depth.

7. PARAMETER OPTIMIZATION AND VERIFICATION OF THE PROPOSED METRIC

Metric parameter optimization and verification has been carried out for the database NRTID[17]. Its main characteristics are presented in Table 3.

Table 3. Test set and subjective experiments

№	Main characteristics	Value
1	Number of images	500
2	Number of observers	316
3	Methodology of visual quality evaluation	Pair-wise sorting (choosing the best visual quality between two considered images)
4	Number of elementary evaluations of image visual quality in experiments	86900
5	Scale of the obtained estimates of MOS	0..11
6	Variance of MOS estimates	1.17
7	Normalized variance of MOS estimates	0.039

Recall that this database contains JPEG format images collected from Internet. The selected images reflect real life situations where there are images with different compression ratios, acquired in good and bad illumination conditions, using macrophotography mode and without it. There are also several computer graphics and animation images. Image size is not the same for all images, it is from 300x400 pixels till 500x600 pixels where horizontal size is smaller than vertical for convenience of pair-wise representation of images at a monitor screen.

Metric parameter optimization and verification have been carried out according to the scheme presented in Fig. 7. Recall that MOS array has been obtained earlier in experiments. Then, it becomes easy to calculate SROCC for any configuration (variable parameter set) of the considered metric.

In fact, we have the following set of variable parameters: K, k, and t in (1), K_b in (2), w_{Cb} = 50 and w_{Cr} in (3). As an optimization criterion, we use SROCC between sharpness metric and MOS to be maximized. The full search method on rough grid has been exploited for optimization at the first stage. Monte-Carlo search in the neighborhood of the obtained starting points has been used at the second stage. Note that SROCC can take only discrete values. Because of this, its maximum is observed not for a unique set of varied parameters but for certain ranges of their values. For example, in the neighborhood of maximum, SROCC is the same for w_{Cb} in the limits from 47 till 53. The same relates to w_{Cr} in (3) that may vary within the limits from 9 till 12. Because of this, we recommend using their values close to the centers of these intervals.

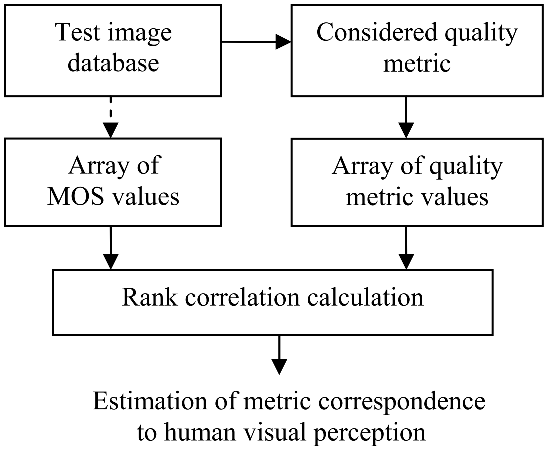

Fig. 7. Block diagram of verification process for metrics of image visual quality

Optimization has demonstrated that it is worth taking into account all effects considered above. For example, optimization of only w_{Cb} and w_{Cr} for original S already leads to SROCC=0.65. If macrophotography mode peculiarities are taken into account, SROCC increases and reaches 0.7. Compensation of blocking artifacts leads to an additional increase of the SROCC that reaches 0.71. This is considerably larger than for other sharpness metrics for the database NRTID[4].

To prove a good correlation between the designed optimized metric and MOS, Fig. 8 presents the scatter-plot of S_{fin} and MOS. Obviously, there is a clear tendency in MOS increase if S_{fin} becomes larger. In fact, the proposed metric directly or indirectly takes into account several factors listed in Introduction. In the first order, it incorporates image sharpness derived from high-frequency DWT coefficients. Besides, it directly takes into account noise level, blocking artifacts and macrophotography effects. Besides, it indirectly takes into consideration image blur (that appears itself in smaller values of high-frequency wavelet coefficients and smaller value of (1)), image color depth and temperature (by assigning larger weights to color components in (3)), image dynamic range (its increase results in larger values of (1)).

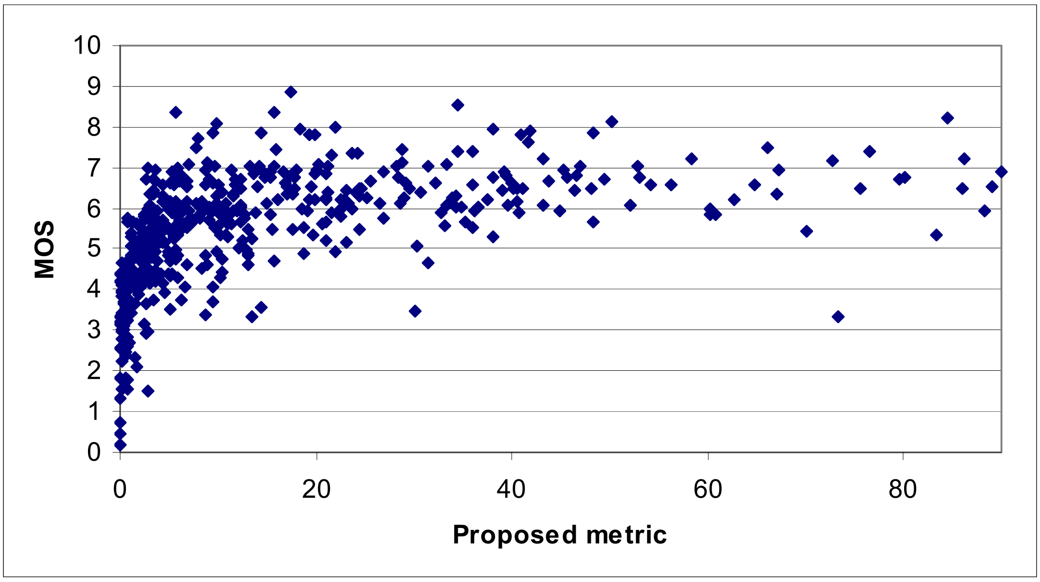

Fig. 8. Scatter-plot of MOS on S_{fin}

CONCLUSIONS ANF FUTURE WORK

The novel sharpness metric for assessment of color image visual quality is proposed. Its parameters are optimized. The obtained results demonstrate that the considered approach to sharpness metric design is quite fruitful since it produces quite high correlation with MOS (SROCC=0.71) although it is still far from unity. This means that image sharpness plays the key role in no-reference assessment of image quality. The proposed metric can serve as a good starting point for further modifications able to incorporate other factors influencing image visual quality.

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