A Matlab-Based Tool for Video Quality Evaluation without Reference

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Abstract. *This paper deals with the design of a Matlab based tool for measuring video quality with no use of a reference sequence. The main goals are described and the tool and its features are shown. The paper begins with a description of the existing pixel-based no-reference quality metrics. Then, a novel algorithm for simple PSNR estimation of H.264/AVC coded videos is presented as an alternative. The algorithm was designed and tested using publicly available video database of H.264/AVC coded videos. Cross-validation was used to confirm the consistency of results.*

Keywords

Quality assessment, GBIM, PSNR, MOS, image quality, H.264/AVC, quality metric.

1. Introduction

Video quality is an important issue for both naive viewers and experts. The viewer naturally wants to receive the highest quality that can possibly be obtained. The achievable quality is usually constrained by the limited bandwidth that is available for transmission, storage, or due to limited capabilities of the terminal (display device). For this reason, it is required to find the threshold, where the perceived quality is sufficient and the needed bandwidth is as low as possible. That is the time where a video quality evaluation comes into the game. The most accurate evaluation of the video quality in the search for such threshold is based on subjective quality assessments, which are able to reveal the real impact of the perceived quality on the viewer. The subjective tests are, however, very time-consuming and costly, and from their nature cannot be used for long term monitoring in an automated system. To account for these drawbacks, a number of objective test methods have been developed, in which the quality rating is calculated automatically. However, the expert must choose the objective metric very carefully in order to get appropriate results.

Objective quality metrics are divided into three groups according to their input data. Typical representative of objective metrics is the very often used Peak Signal to Noise Ratio (PSNR). This metric needs both original and distorted image in order to be computed. Therefore it is a full-reference method (FR). Other FR metrics are e.g. SSIM [1] based on Structural Similarity or Image Evaluation based on Segmentation CPqD-IES [2] of the Brazilian Center for Research and Development (CPqD). Then there are so called reduced-reference (RR) approaches, when we have just some reduced information about the original image. Examples of reduced reference metrics can be found e.g. in [3] or [4]. One of the most progressive approaches are no-reference metrics. These do not need any information about the original image or video. Therefore, they can be used in cases, where the FR and RR metrics can not be, e.g. at the end of the video distribution network, where the original undistorted data are often not available.

No-reference video quality evaluation can be performed in two domains, in the pixel domain or using information acquired from the bitstream of the coded video. Some of possible approaches are mentioned in Sections 3 and 4.

In this paper, we present a Matlab-based Tool for No-Reference Video Quality Evaluation. The idea of creating a video quality tool is not novel. The authors of [5] presented a Matlab tool for image and video quality evaluation. However, no-reference approaches are available for images only and video quality evaluation can be performed solely as full-reference. Also the variety of input video formats is reduced (depends on installed codecs). Another video quality measurement tool is presented by Yoockin and Ratushnyak in [6]. Their tool supports a wide range of input formats and quality metrics. However, it supports full-reference metrics only. Another tool is proposed by the authors of [7]. Their tool is implemented in C++ using the OpenCV library, which offers better performance compared to Matlab based implementations. Unfortunately, similarly to the other tools, only full-reference measurements are supported by the software.

The video quality evaluation tool presented in this paper uses two existing pixel-based metrics for NR quality evaluation and a new proposal of a simple bitstream-oriented metric for estimation of the PSNR of H.264/AVC coded sequences.

The paper is organized as follows: Section 2 describes the development of No-Reference Video Quality Tool (NR

VQT) and presents the tool as a whole. In Section 3 we describe pixel-oriented approaches used in NR VQT. Section 4 introduces the simple PSNR estimator for H.264/AVC coded sequences as a part of our tool. Section 5 then shows the results of objective video tests using proposed No-Reference Video Quality Tool.

2. No-Reference Video Quality Tool

The NR Video Quality Tool was created in order to offer the users a simple and intuitive environment for performing video quality testing without using reference sequence. The GUI of our tool is shown in Fig. 1. The tool is programmed in Matlab environment in order to allow for easy addition of new features (e.g. new metrics). The NR VQT is developed to handle a wide range of video formats.

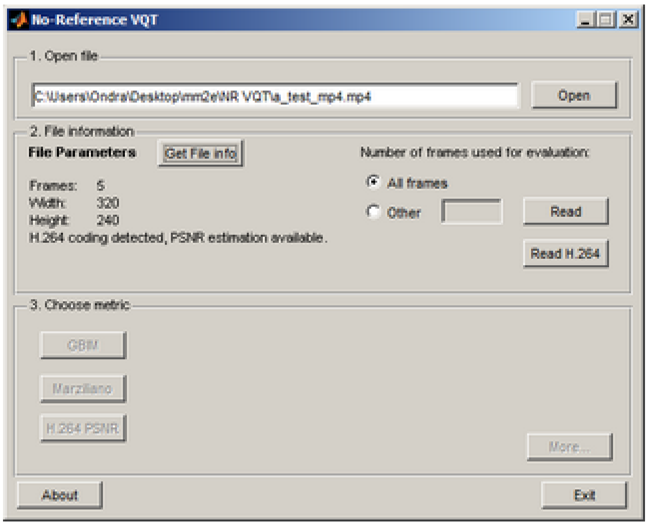

Fig. 1. Graphical interface of the proposed tool.

For video decoding we do not use the Matlab built-in functions, because they can not guarantee 100 % compatibility on different machines. We use FFmpeg encoder[1] instead in order to extract luma component from the input video. All major pixel-based approaches use this component only and therefore it is considered satisfactory for our purpose. Afterwards, the luma data is read by Matlab from binary file. This modification allows us also to increase the computational speed (compared to [5]). This implementation also allows the possibility of additional processing if desired. FFmpeg also provides decoding to the Annex B bytestream format for H.264/AVC coded videos as this format is needed for further processing, as described in Section 4.1. The user can choose the number of frames he wants to run the metric on. Also if the input video is coded using the H.264/AVC standard, the user is informed about this fact and has the opportunity to use the H.264/AVC PSNR Estimation.

For measuring quality, we use both pixel-oriented and bitstream-oriented approaches. As representatives of pixel-domain metrics we chose Generalized Block-Edge Impairment Metric (GBIM) as described in [11] and metric for perceived blur proposed by Pina Marziliano et al. in [10]. The metrics implemented in the tool so far are presented in Sections 3.1, 3.2 and 4.1.

[1]http://www.ffmpeg.org

After computation, the results are shown in the lower part of the GUI as shown in Fig. 2. The output of the calculation is one number representing the quality of the whole sequence. We display the mean value of the quality coefficients among all frames, as well as other statistical values.

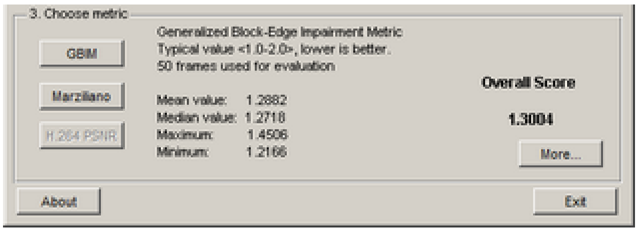

Fig. 2. Displaying results, NR VQT.

The main information about the quality is displayed as Overall score. This value is computed using Minkowski summation. This algorithm is representative of temporal pooling methods. Such an algorithm computes one overall value which should correlate with the subjective assessment of quality. The description of the algorithm of Minkowski summation can be found e.g. in [8]. The Minkowski parameter was chosen according to the recommended value $p = 10$. We also tested several other temporal pooling methods, which are described in [9]. These methods were not finally implemented in the on-line available version of the SW. Temporal pooling methods can improve performance of a quality metric, however it should be considered if the difference between pooled values and conventional mean values compared to subjective tests is significant enough to implement more complex temporal pooling methods.

3. Pixel-Oriented Approaches

No-reference metrics are usually designed to detect one specific type of distortion in the image. The most common distortion types in compressed digital video are blocking artifacts and blurriness. Blocking artifacts are usually a result of high degree of compression. Practically all mainstream video compression algorithms divide the coded picture in smaller blocks, which are then coded separately using prediction and transform coding. However, on the edges of these blocks, a perceivable difference may appear and is then recognized as distortion by the viewer. Another important distortion, blurriness, may appear as a result of coarse quantization when higher spatial frequencies are attenuated (or even neglected) and the information about details in the picture is lost.

Although the recent video coding algorithms employ adaptive filters to fight blocking artifact, the result of such filtering after a strong compression is basically a trade-off between blockiness and bluriness. Intuitively, measuring these values for a compressed video makes a good basis for no-reference quality estimation.

3.1 Measuring Blurriness

The authors of No-Reference Perceptual Blur Metric, [10], suggested that in pixel domain, we can detect blurriness by measuring the width of the edges. Wider edges can than be considered as an edge affected by the smoothing effect of the blur. The flow chart of their metric is shown in Fig. 3. The *NbEdges* is the total number of edges and *TotBM* represents the total blurriness measure. According to the authors, the metric is near real-time and does not depend on the content of the image.

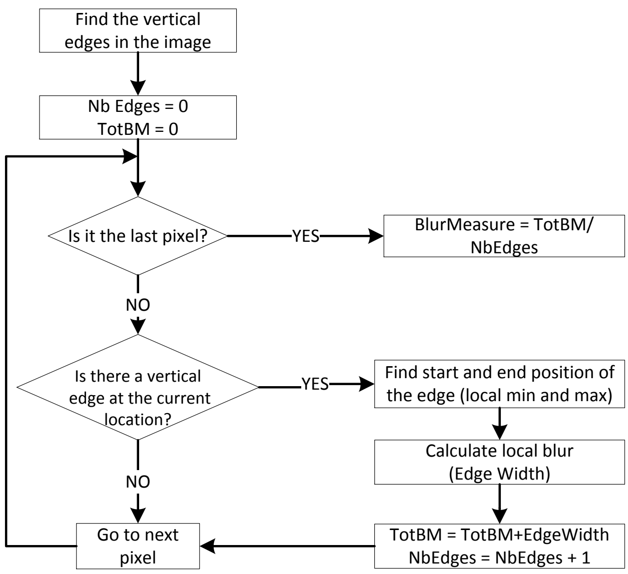

Fig. 3. Flow chart of the No-Reference Perceptual Blur Metric as proposed in [10].

3.2 Generalized Block-Edge Impairment Metric

In Generalized Block-Edge Impairment Metric (GBIM), [11], the authors suggest that blocking artifacts are considered as sudden changes in luminance on the edges of adjacent blocks. The image is then defined as $\mathbf{f} = \{\mathbf{f}_{c1}, \mathbf{f}_{c2} \cdots \mathbf{f}_{cNc}\}$, where $\mathbf{f}_{cj}$ is the j-th column of the image with a total number of N_c columns. The column difference is then given by

$$D_c\mathbf{f} = \begin{bmatrix} \mathbf{f}_{c8} - \mathbf{f}_{c9} \\ \mathbf{f}_{c16} - \mathbf{f}_{c17} \\ \vdots \\ \mathbf{f}_{c(Nc-8)} - \mathbf{f}_{c(Nc-7)} \end{bmatrix}. \tag{1}$$

The metric for measuring horizontal blockiness is then defined by

$$M_h = \|\mathbf{W}D_c\mathbf{f}\| \tag{2}$$

where $\mathbf{W}$ stands for a diagonal weighting matrix. This function represents masking of the block structure in very bright or dark areas by the Human Visual System. The weighting algorithm is not be further described and can be found in [11]. The authors tested their metric on a database of MPEG-1 coded videos and their filtered alternatives. Although PSNR for both variants were similar, GBIM values had higher range and therefore could describe blocking artifacts more precisely then conventional full-reference PSNR metric compared to subjective tests.

4. Bitstream-Oriented Approach

The above mentioned methods use computation in the spatial (pixel) domain. Therefore, the video must be decoded completely. This may not be always suitable and in some cases even possible. Bitstream-oriented approaches remove this disadvantage. On the other hand such a bitstream metric is suitable for one specific coding algorithm only. One of the first bitstream-oriented methods for quality measurement of MPEG-2 coded videos has been proposed in [13]. The authors proved that PSNR can be derived from the probability distribution function of the transform coefficients. Simply by counting the number of coefficients that are quantized to zero, they can estimate the distribution of the coefficients. Similarly in [14], a metric for H.264/AVC coded videos is proposed. The distribution of transform coefficients is considered as Laplacian. By counting the zero coefficients and extracting the quantization parameter, the parameters of distribution can be calculated. Finally, MSE in frequency domain can be derived, which is due to Parseval's Theorem equivalent to the MSE in spatial domain. The resulting PSNR is then computed the by well-known formula [14]

$$PSNR = 10 \cdot \log_{10}\left(\frac{m^2}{MSE}\right) \tag{3}$$

where m stands for the maximum value of pixel (typically 255 for pictures with 8-bit depth). A similar approach for H.264/AVC coded videos was presented in [15], where the authors suggested Cauchy distribution of the coefficients.

In [17], a different approach was suggested. The authors built up their metric on information about frame rate, quantization parameter and motion vectors. All the calculations are very simple, therefore the metric can be used in real-time operation. According to [17], the metric achieves Pearson Correlation Coefficient (PCC) value of 0.894, which is slightly better than the often used FR Temporal MOVIE metric [18]. Other approaches often use neural network to train the algorithm to estimate the quality. An example of such an approach can be found in [16].

4.1 Simple PSNR Estimator

Based on the findings mentioned above, we propose our simple PSNR estimation algorithm for H.264/AVC coded videos. We assume, that the main information about the video quality is carried by quantization parameter (QP) and the number of zero transform coefficients. These will be the inputs to our metric. It can be observed, that the slices with lower number of zero transform coefficients usually have higher PSNR value. This corresponds to the theory of H.264/AVC coding, when higher count of zero coefficients represent attenuation of higher spatial frequencies (especially for I slices) and this may lead to the loss of details in the picture. However, this relation may depend on the content of the scene and an algorithm based only on this information may underestimate the quality of videos with uncomplicated contents.

For acquiring QP and number of zero transform coefficients we use a modified JM H.264/AVC decoder[2]. This decoder enables us to generate a XML file during decoding, containing information from bitstream, e.g. QP, values of transform coefficients, motion vectors, etc. The decoder needs as its input a H.264/AVC coded video in Annex B bytestream format, therefore some preprocessing may be needed. For our purpose, the source code of the decoder was modified to provide only the needed information. We disabled decoding video to picture data, writing transform coefficients of chroma components and motion vectors. We also changed the way of writing out luma component coefficients. Instead of writing all coefficients of a macroblock, we use just the number of zero coefficients for each macroblock. This led to approximately 10-fold increase of the decoder speed. Accordingly, the size of the generated XML file decreased significantly. The XML data are then read into Matlab environment for further processing. This approach may look a bit complicated at first sight, but it enables the user to have insight in the coded data and better understand the dependence between the bitstream and perceived quality.

For our experiments we chose the video database created by the authors of [19]. This database offers 12 source sequences in CIF resolution (352x288). These sequences where encoded with the Reference JM encoder using a wide range of bitrates to create 56 coded sequences altogether. The database is available on-line[3] also with results of subjective scores. The description of the content of the sequences is in Tab. 1. To the best of our knowledge, there is no other suitable and publicly available database including both the compressed AVC bitstream and corresponding MOS scores, therefore the algorithm was tested on the above mentioned database only.

Each of the source sequences is encoded with 4 or 6 different bitrates varying from 32 kbps to 2048 kbps. Sequences have 300 frames and GOP length of 15 frames. The first frames of all the used sequences are shown in Fig. 5.

As mentioned earlier, we use average QP and the number of zero transform coefficients as inputs to our algorithm. The main information about the quality is given by the Quantization Parameter QP. In Fig. 4 the correlation between average QP of the whole sequence and PSNR is shown.

Name	Description
Australia	Still camera, talking person
City	Camera rotation, city buildings
Coastguard	Moving camera, coastguard on water
Container	Still camera, cargo ship
Crew	Moving camera, welcoming a spaceship crew
Football	Fast moving camera, American football
Foreman	Talking person, moving camera
Mobile	Various moving object, moving camera
Silent	Person showing sign language, still camera
Stephan	Tennis player, moving camera
Table-tennis	Zooming camera, cut
Tempete	Storm, zooming camera

Tab. 1. Characteristics of used test sequences.

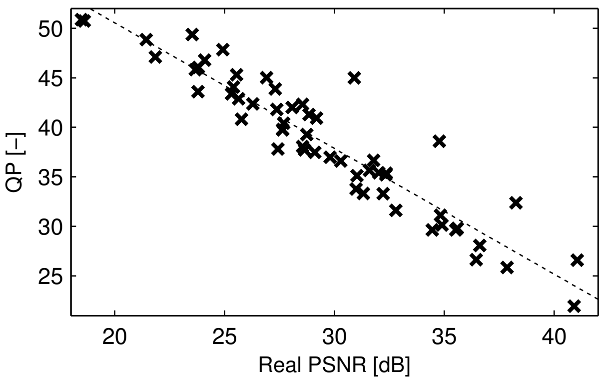

Fig. 4. Correlation of real PSNR value and average QP per sequence.

The situation gets much more complicated when the number of transform coefficients quantized to zero is high. B and often also P slices usually had all coefficients quantized to zero. This does not, however, have to necessarily influence the perceived quality (depending on the content of the video). Therefore such simple approach as with the QP was not possible. Anyway, it was found that statistical information acquired from the counts of zero coefficients may provide overall information about the total quality. We primarily use the most frequent value of zero coefficients and its numerousness together with variation and standard deviation. These values with the real PSNR values were the inputs of the standard Matlab linear regression function. The final PSNR is then defined by

$$PSNR = c_1 \cdot QP + c_2 \cdot mod(Z) + c_3 \cdot num(Z) + \\ + c_4 \cdot std(Z) + c_5 \cdot var(Z) \quad (4)$$

where c_1 to c_5 are coefficients of the regression. The variable QP represents average Quantization Parameter, the Z-variables then the most frequent value and its numerousness,

[2]http://vqegstl.ugent.be/?q=node/14
[3]http://amalia.img.lx.it.pt/~tgsb/H264_test

(a) Australia **(b)** City **(c)** Container **(d)** Coastguard **(e)** Crew **(f)** Football

(g) Foreman **(h)** Mobile **(i)** Silent **(j)** Stephan **(k)** Table-tennis **(l)** Tempete

Fig. 5. Testing sequences.

standard deviation and variance of the count of zero transform coefficients respectively. Thorough analysis showed, that the mode along with its numerousness have the most significant impact on the final PSNR. We also experimented with the traditional mean of the count of zero coefficients but these results were not satisfying. The standard deviation and variance then serve to improve the final result. This estimated PSNR then symbolizes the PSNR of the whole sequence. Computing PSNR for each frame using this approach may be used for intra coded slices only, for other slice types some extension of the algorithm would be necessary.

5. Objective Tests

Our tool was used for objective measurements of the video quality of H.264/AVC coded videos. Firstly, the PSNR estimating algorithm was trained to learn the dependencies between given values from the bitstream and the real PSNR value. We also used leave-one-out crossvalidation to improve our results. After crossvalidation, our metric shows the Pearson Correlation Coefficient of 0.94. For crossvalidation purposes, we removed sequences belonging to one of the source sequences from the group and used the rest as input of the regression. Resulting regression coefficients were then used in the formula 4 and the estimated PSNR of previously removed sequences were computed. The results for crossvalidation are shown in Fig. 6. Our results also showed, that the algorithm estimates the PSNR most accurately for the middle range of the bitrates. For lower bitrates, the algorithm usually underestimates the real value, for higher bitrates the metric usually overestimates the value. The average absolute error is 1.31 dB. Considering that our metric is regarded as a simple and quick estimator, these results are satisfactory.

In Fig. 7 it is shown how the average error of the estimated PSNR using our algorithm depends on bitrates used for encoding the video. We chose only bitrates for which more then four sequences were available. We show regular mean values and mean values of the absolute values of the difference of the PSNR. It can be seen, that the algorithm is most accurate for bitrate ranges from 128 to 256 kbps.

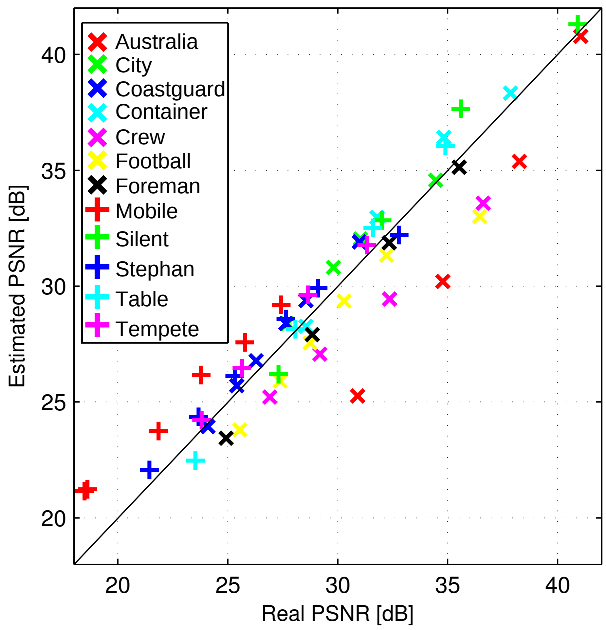

Fig. 6. Comparison of the estimated and real values of PSNR.

As can be seen from Fig. 6, the results approximately converge to the the line $y = x$.

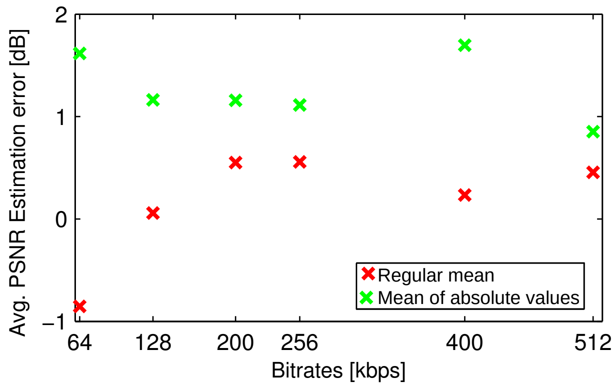

Fig. 7. Average estimation error in comparison to used bitrates.

5.1 Comparison with Subjective Measurements

The used database also offers values of subjective measurements MOS. For the purpose of subjective test, 42 participants rated the quality of the video sequences. The participants were non-experts between the age of 23 to 32, both male and female. Sequences were evaluated in two testing groups, some sequences were common for both of groups. Fig. 8 shows the relation between MOS and real and estimated PSNR. The doted line represents linear fit of real PSNR values. It can be seen, that PSNR values estimated by our algorithm correspond to the MOS values. Correlation coefficient for chosen data are shown in Tab. 2.

Finally, we improved the algorithm in order to estimate MOS directly. The MOS estimation is based on the same approach as the estimation of the PSNR. The main change is the use of real MOS values as a input of the linear regression function. After the regression, a new set of coefficients is obtained and these are used similarly as in (4). After cross-validation we obtained results as shown in Fig. 9. The MOS estimation was then also implemented in the software.

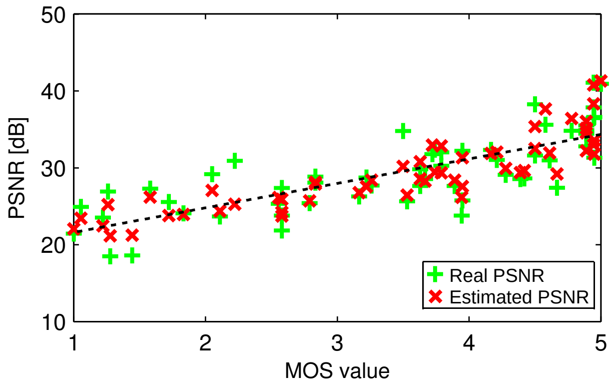

Fig. 8. Comparison of MOS and PSNR.

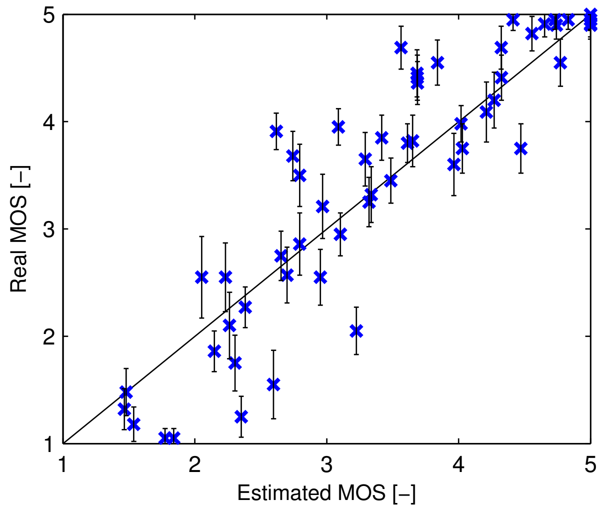

Fig. 9. Real and estimated MOS values.

Correlation	Pearson	Spearman
$PSNR_{real}$ & $PSNR_{est}$	0.941	0.939
MOS_{real} & MOS_{est}	0.897	0.908
MOS_{real} & $PSNR_{est}$	0.862	0.903

Tab. 2. Correlation of the results.

6. Conclusion

In this paper, we presented a Matlab based tool for no-reference video quality evaluation. The tool supports wide range of input video formats. For NR quality evaluation the user can use two pixel-based metrics. We also implemented our algorithm for simple estimation of the PSNR and MOS of H.264/AVC coded videos. Our metric uses information from coded bitstream only. The results show the Pearson's correlation coefficient of 0.94 for real PSNR values. Next we modified the algorithm to obtain estimation of MOS. This estimation shows correlation coefficient of 0.90. The tool can be further improved implementing other NR approaches. The simple PSNR and MOS estimating algorithm can be improved adding more features to consider in determining the quality. At this state, the tool can serve as quick tool for determining the quality of short sequences. The tool is available for download at http://www.urel.feec.vutbr.cz/index.php?page=software .

Acknowledgement

Research published in this paper was financially supported by the project CZ.1.07/2.3.00/20.0007 WICOMT of the operational program Education for Competitiveness. The work on this paper was also supported by the project CZ.1.07/2.3.00/30.0005 of Brno University of Technology, by the Czech science foundation under project number P102/10/1320 and by the Czech Ministry of Education under grant number LD12005. The described research was performed in laboratories supported by the SIX project; the registration number CZ.1.05/2.1.00/03.0072. Publication of the results was financially supported by the project Popularization of BUT R&D Results and Support of Systematic Collaboration with Czech Students, no. CZ.1.07/2.3.00/35.0004.

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