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The Impact of Quality of Service Parameters to the Subjective and Objective Video Quality Assessment

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Abstract: This paper deals with the delay, delay variation – jitter, packet loss rate and bandwidth as quality of service parameters, in the form of four types of video quality degradations. The impact of defined levels of degradation on subjective impressions (given as mean opinion scores) is analyzed. ReTRiEVED video dataset with publicly available subjective scores is used in the analysis. Three full-reference measures are used for objective assessment of video quality. The degree of consistency of subjective and objective quality scores is shown through scatter plots and quantitative measures (linear correlation coefficient and correlation of the ranks). Based on the interpolation functions, quality of service parameters are mapped to subjective experience. We show that jitter is a much more destructive effect than other degradation types.

Keywords: Jitter, Packet loss rate, Quality of service, Subjective and objective video quality assessment.

1 Introduction

Development of multimedia devices (smart phones, tablets, etc.) and progress in telecommunication infrastructure with available broadband technologies have led to an exponential increase in demand for high-quality multimedia services. The use of mobile devices will increase by more than 80% in 2020 compared to 2010. The trend of further growth will continue, so in 2025 the growth will be by more than 175% compared to 2020. The volume of traffic transfer generated by mobile devices will exceed 50% of overall network traffic, while transmission requests will be doubled in 2018 [1]. On the other hand, wireless networks are susceptible to the changes in the network environment, and therefore transmission errors occur. In network-limited video transmission, it is crucial to maintain high video quality. Quality of transmission is usually defined using QoS (Quality of Service) parameters (bandwidth, delay, jitter and packet loss rate). The key parameters in a traditional, network-oriented

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approach to video quality analysis, are packet loss rate and delay. However, this approach is not complete because it does not take into account the end users (human) experience. For these reasons, service providers must ensure a suitable strategy for monitoring and adjusting the quality of the received signal in order to maintain their SLA (Service Level Agreement). Therefore, a modern network approach involves the use of QoE (Quality of Experience) measures, or the estimation of end users satisfaction.

The traditional approach expressed through QoS is well known and relates to network performance. QoS can be defined as the overall performance of telecommunication networks and services that ensure the satisfaction of the defined requirements and needs of end users. Contrary to that, QoE is still an active field of research. This term refers to the description of quality as perceived by the end user, i.e. the viewer, with the emphasis on the perceptual quality of visual content [2]. A subjective quality assessment, although more reliable, is time-consuming and requires subjective testing, as well as additional time to process and analyze the test results. As such, it is unsuitable in real-time applications. The results of such tests are average observers ratings, given as mean opinion scores (MOS). Furthermore, QoS parameters measuring, is an automatic process for the operators, but it does not reflect the level of quality observed by the end users. So, the analysis of network performance expressed in QoS form only is not complete without subjective assessments. For this reasons, it is very important to analyze the relation between objective QoS parameters (network performance measure) and the corresponding QoE subjective measure (subjective quality of the delivered video content).

2 ReTRiEVED Video Sequences Dataset and the Effects of Transmission Impairments on Perceived Video Quality

Video quality may be affected by transmission impairments, such as delay, jitter, packet loss and bandwidth. ReTRiEVED video sequences dataset is designed by considering these network impairments. Along with dataset description, in this section we illustrated the effects of transmission impairments on the perceived quality of the video.

ReTRiEVED video sequences dataset that we will use in experiments contains 184 video sequences (8 source sequences and 176 test sequences). Test sequences were obtained by sending original (source) sequences from the VideoLAN server (with MPEG-2 compression for 9 Mbps and UDP protocol) through a noisy channel that is simulated using NetEM (Network Emulator) software. On the receiving side, VLC Player was used to record the data in the TS (Transport Stream) format and to display the video sequences to the viewers [3]. Frame dimensions in this dataset are 704x576 and 720x576 pixels.

Although most of the publicly available video datasets contain H.264/AVC coded sequences, the ReTRiEVED dataset contains the still popular MPEG-2 coded video signals, since MPEG-2 is the basis of some diffusion and streaming services such as VoD (Video on Demand). In addition to video materials, subjective quality scores are also available [4].

For each original sequence, 22 test sequences with degradations were generated. Four types of degradations were analyzed: delay (D), jitter (J), packet loss rate (PLR) and bandwidth-limited transmission (B). Selected types of degradations are basic QoS parameters [5]. The values of degradation parameters used in the experiments are based on the ITU and ETSI recommendations and their values are given in **Table 1**.

Table 1
Degradation parameters used in a ReTRiEVED dataset.

Delay [s]	0.1	0.3	0.5	0.8	1		
Jitter [ms]	1	2	3	4	5		
Packet loss rate [%]	0.1	0.4	1	3	5	8	10
Bandwidth [Mbps]	0.512	1	2	3	5		

Fig. 1 shows example frames of original and test sequences. Introducing the delay, each packet is uniformly delayed and the quality of the rendered video has not been changed. Jitter and packet losses, as well as the bandwidth-limited transmission lead to blocking effects, line degradations and color artefacts (Figs. 1c – 1e), which significantly reflects on subjective impressions.

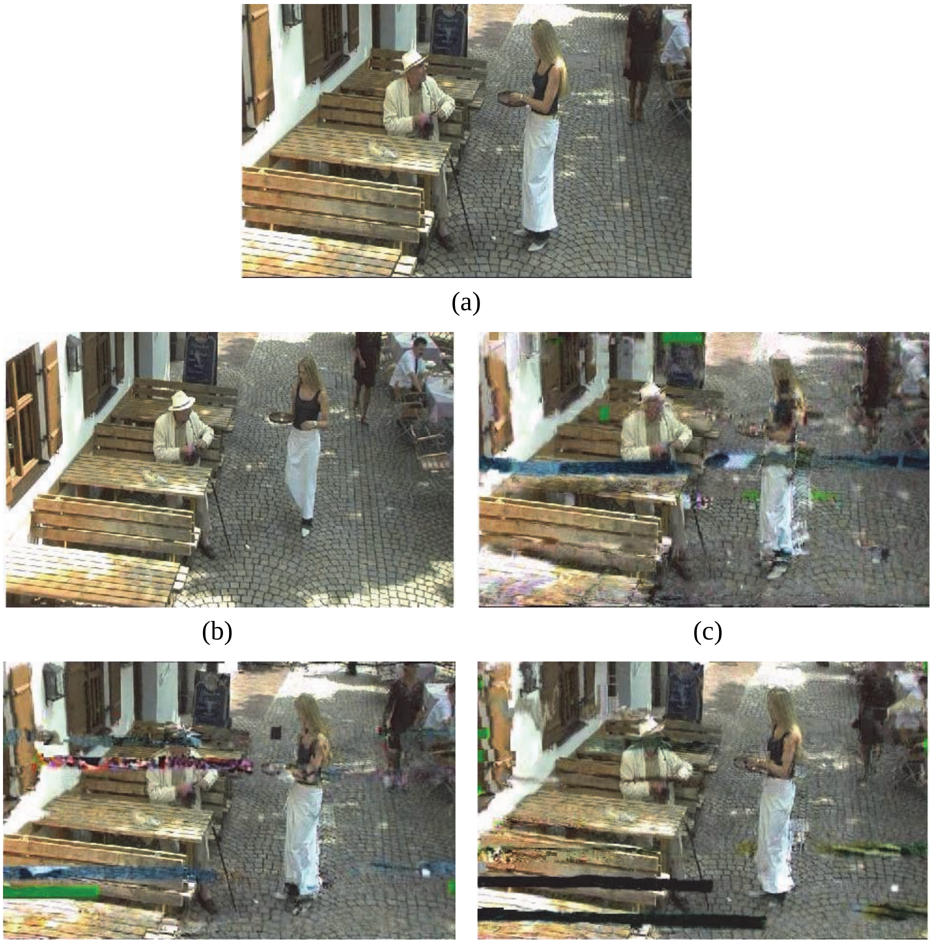
To better understand the visual effects caused by different degradation levels, Figs. 2 – 4 show example frames extracted from the original and test video sequences affected by jitter, Fig. 2, packet loss, Fig. 3, and limited bandwidth, Fig. 4.

For high values of jitter (larger than 2 ms), visual quality is very poor, i.e. perceptual quality decreases significantly. Higher values of PLR produce higher signal degradations and human satisfaction of provided signal is low. Also, as expected, when available bandwidth reduces, the visual quality decreases.

3 Analysis of Subjective Tests Results

Subjective tests were performed according to ITU recommendations that define testing conditions, criteria for selection of observers and test materials, assessment procedures, etc., in order to ensure reliable results. Forty-one observers participated in the subjective tests. The tests were conducted according to ACR-5 (Absolute Category Rating) methodology, where the observers had five possible options for quality evaluation: 1 – very bad, 2 – poor, 3 – fair, 4 – very good and 5 – excellent.

The results of subjective tests are viewers' quality observations, presented through average subjective scores (MOS). MOS is a simple arithmetic mean of all the scores assigned to a test video sequence.



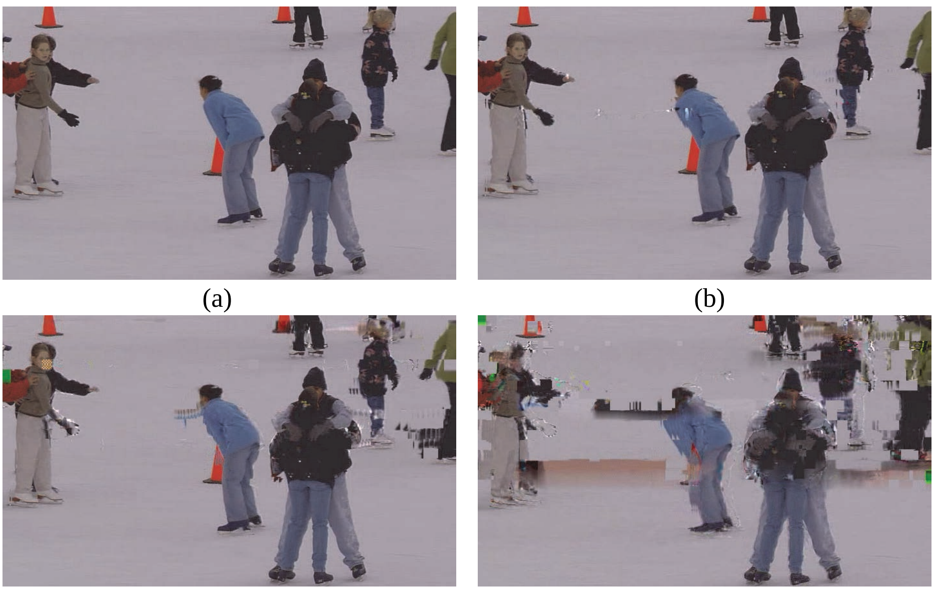
(a) (b) (c) (d) (e)

Fig. 1 – *Example frames of the sequence "Restaurant" and test sequences: (a) original (MOS=4.66); (b) delay (D=1 s, MOS=4.46); (c) jitter (J=2 ms, MOS=1.12); (d) packet loss rate (PLR=10 %, MOS=1.49); and (e) limited bandwidth (B=1 Mbps, MOS=1.57).*

Fig. 5 shows the impact of different types of degradations on subjective quality impressions by the original sequences.

(a) (b) (c) (d)

Fig. 2 – *Example frames of the original sequence "Soccer" and test sequences affected by jitter (in ms) and their corresponding MOS values*: *(a) original, MOS=4.32*; *(b) J=2 ms, MOS=1.37; (c) J=3 ms, MOS=1.20; and (d) J=5 ms, MOS=1.02*.



(a) (b) (c) (d)

Fig. 3 – *Example frames of the original sequence "Ice" and test sequences affected by different PLRs (in %) and their corresponding MOS values*: *(a) original, MOS=4.34*; *(b) PLR=3%, MOS=2.22*; *(c) PLR=8%, MOS=1.63*; *and (d) PLR=10%, MOS=1.37*.

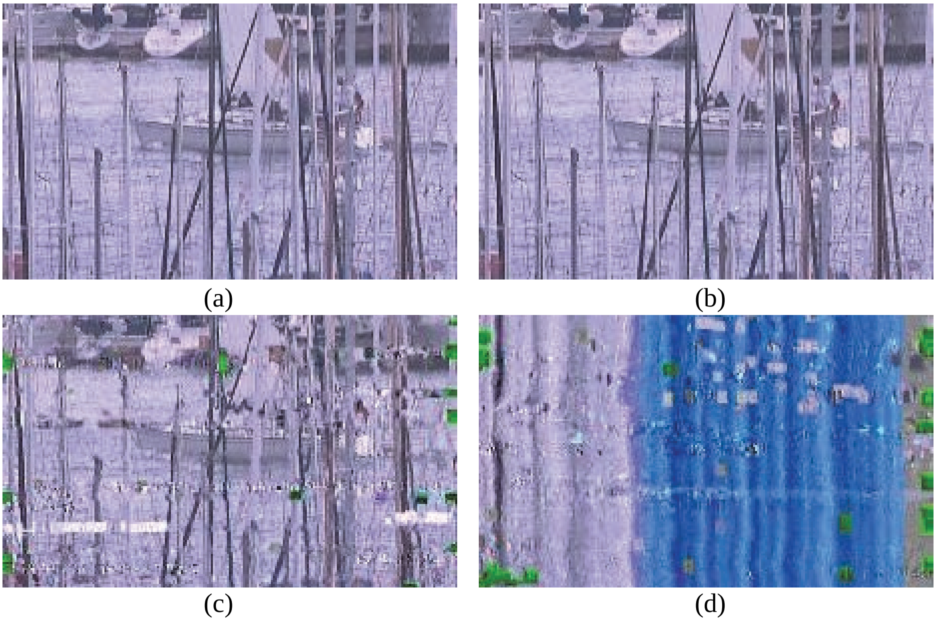


Fig. 4 – *Example frames of the original sequence "Harbour" and test sequences affected by bandwidth limited transmission (in Mbps) and their corresponding MOS values*: *(a) original, MOS=4.27*; *(b) B=5 Mbps, MOS=4.13*; *(c) B=1 Mbps, MOS=1.60*; *and (d) B=0.512 Mbps, MOS=1*.

Fig. 5a shows that as expected, observed quality does not depend on the initial delay. This confirms that subjective tests were reliably performed. Furthermore, it can be concluded that subjective quality impression depends on the content of video sequences. Delayed "Park joy" sequences were poorly rated by the observers while "Restaurant" sequences (Fig. 1) are rated better.

Jitter adversely affect observers' satisfaction with visual content, that is, with increase in jitter to 3 ms subjective ratings decrease significantly (Fig. 5b). Further increases in the jitter, result in poor, around 1 (very poor quality), but approximately constant subjective ratings.

If the packet loss rate is lower, the average rating of the observers is higher (Fig. 5c). With an increase in packet loss rates up to 5%, the observers' satisfaction rapidly decreases, and after that satisfaction also falls, but slower.

For a small bandwidth of the transmission system, quality scores are also small (Fig. 5d). With increasing bandwidth, up to 2 Mbps, there is a linear increase in the perceived quality (MOS), after which the subjective impressions remain almost constant.

Figs. 5b – 5d also show the mapping functions, selected as optimal in previous research of QoS parameter mapping into subjective (QoE/MOS) impressions [1, 6]:

$$QoE(J) = 16.7e^{-1.957J} + 1.097\,, \tag{1}$$

$$QoE\left(PLR\right) = -0.5096\log_e PLR + 2.57\,, \tag{2}$$

$$QoE(B) = 4.059 / \left(1 + e^{-2.475(B-1.051)}\right). \tag{3}$$

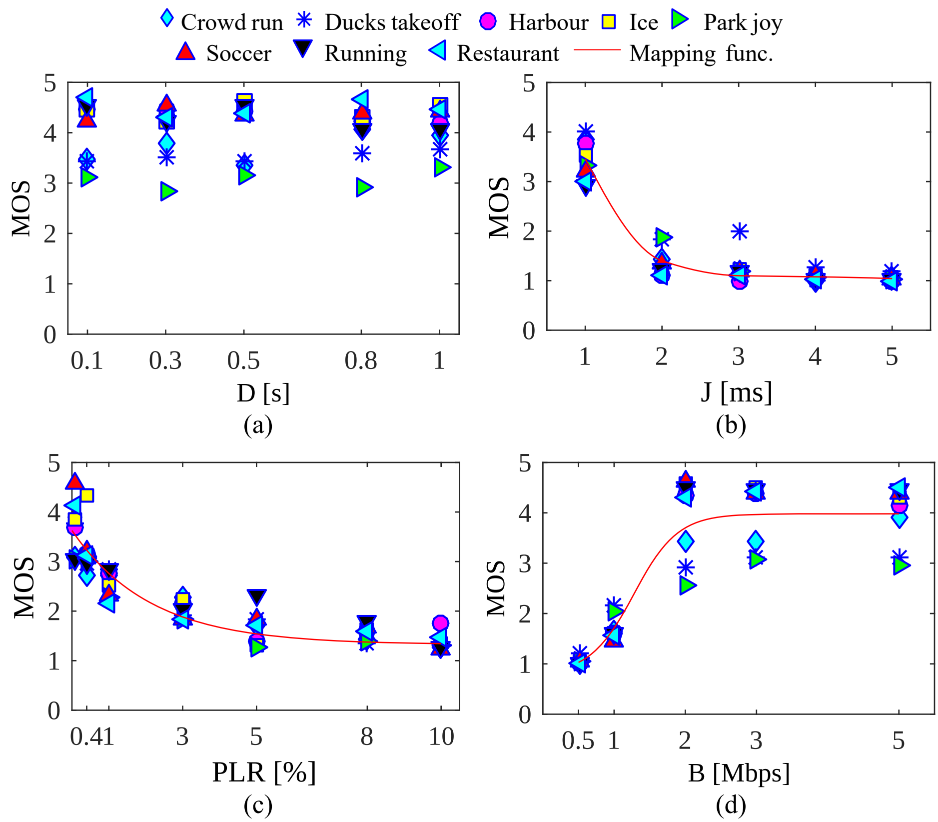


Fig. 5 – *The impact of different types of degradations on subjective quality impressions: (a) impact of delay on MOS; (b) impact of the jitter on MOS; (c) impact of packet loss on MOS; and (d) impact of bandwidth on MOS.*

4 Performance Analysis of Objective Video Quality Assessment Measures

Many publicly available datasets contain registered source and test sequences both in time and field of view (space). However, this is not the case in the ReTRiEVED dataset, with temporal discrepancies due to misalignments between source and test sequences. Poor registration leads to full-reference objective metrics systematically underestimating objective quality of test sequences and consequently poor evaluation performance. In order to estimate test sequence objective quality reliably, we adopted a two stage approach: temporal registration and objective video quality assessment. Temporal registration is based on an exhaustive search of temporal shifts in a limited, discrete range around the original estimate. Once the optimal temporal shift is found it is applied to the test sequence to produce a registered test sequence, which is then compared to the original source sequence using three objective measures (objective quality assessment stage).

4.1 Temporal registration

Degradations during acquisition, compression, processing, transmission and reproduction may include temporal delays and changes in temporal sampling patterns as well as geometric deformations such as field of view changes, e.g. reductions in the visible field of view. Temporal aberrations affect the entire data stream and can move the displayed sequence by several frames from the actual events observed by the sensor. Geometric deformations, such as perspective changes in the field of view are introduced as artefacts of the coding and transmission system [7, 8].

Such systematic aberrations in the test compared to reference video signals are automatically corrected by the human visual system and generally disregarded in subjective estimates of video quality. This leads to a bias in objective quality estimates compared to subjective ones.

Temporal registration aims to correct temporal shifts introduced between the source and the test sequences. In order to efficiently solve a relatively complex optimisation problem that is the temporal matching of two sequences, the test sequence is compared to the original source sequence in the time domain and an optimal time shift of the test sequence is sought that would minimise the temporal discrepancies between the events in the two sequences.

The temporal registration algorithm seeks an optimal alignment parameter – the optimal time shift. The set of possible time shifts is discrete and limited by the lengths of the sequences. In reality, however, this set is even narrower and it is reasonable to expect that the true shift will only be several frames in either direction from the initial estimate. For this reason, it is practical to use the simplest and least efficient optimisation strategy: exhaustive search to find the optimal time shift. This would ensure that the optimum is not skipped and the process does not get stuck in a local minimum.

For each possible shift, the distance between the two sequences is measured and the shift that results in the smallest distance is chosen as the optimum. The distance is measured on the valid temporal overlap of frames determined by the shift.

Fig. 6 – *(a) A frame from the original sequence; (b) optimal time shift for test sequence using absolute differences in intensity; (c) the frame at the corresponding time point in the test sequence; (d) abs difference metric between non registered source (top) and test (left) images; (e) the proposed matching frame by the sum of absolutes temporal registration at delay of -2; and (f) abs difference metric between registered source (top) and test (left) images.*

Temporal registration algorithm was implemented using a simple and robust sum of absolute intensity differences (SAD) distance measure. The measure applied to the intensity channel of source original and test sequences in the ReTRiEVED dataset ("Crowd run" sequence), is illustrated on Fig. 6. A frame from the original sequence, Fig. 6a, is shown alongside two frames from the test sequences (Figs. 6c and 6e). The frame in the middle, Fig. 6c, is the corresponding frame in the test sequence to the frame in the original sequence. Fig. 6b shows the optimisation surface obtained using the adopted objective metric, against shift between source and test sequences. The simple SAD distance applied to the intensity channel produces a robust result with a deep trough around the minimum (–2). The frame on Fig. 6e is the one proposed as the matching frame by temporal registration. The absolute distance image shown on Fig. 6d clearly identifies temporal differences between the images, while this is significantly reduced compared to the registered frame with residual small differences on Fig. 6e due to additional degradation (in this case limited bandwidth, B = 5 Mbps).

Evaluation results on ReTRiEVED video sequences indicate a high level of robustness of this process, since the objective quality assessment measures provided much better agreement with subjective scores using registered sequences than using delivered, unregistered sequences.

4.2 Objective video quality evaluation

Using temporally registered sequences we analysed the performance of three full-reference objective video quality assessment metrics: Peak Signal to Noise Ratio, PSNR [9], Structural Similarity Index, SSIM [10], and gradient-based objective video quality assessment metric, VQ^{AB} [11].

PSNR is one of the most commonly used objective measures but often criticized for providing results that are not fully consistent with subjective quality assessments.

With SSIM objective measure, the image degradation is viewed as a perceptual loss of structural information, as opposed to the traditional approaches which focus on the difference in intensity (such as PSNR). In cases of PSNR and SSIM measures, the objective quality assessment is primarily defined at the frame level (luminance component only), and consequently the averaging of these localised values is performed to reach the final quality scores, Frame PSNR and Frame SSIM. The objective VQ^{AB} measure can also be considered as structural approach which relies on the evaluation of preservation of structural information between the source and test sequences. In addition to the preservation of structural (still frame) information, VQ^{AB} also takes into account the preservation of temporal and chromatic information [11].

Performance of the objective metrics was evaluated with respect to two aspects of their ability to estimate subjective assessment of video quality: prediction accuracy – the ability to predict the subjective quality ratings with low error, and prediction monotonicity – the degree to which the metrics' ratings agree with the relative magnitudes of subjective quality ratings [12]. We adopt two measures of metric performance. The first is the Linear Correlation Coefficient, LCC, which provide an evaluation of prediction accuracy. The second is the Spearman Rank-Order Correlation Coefficient, SROCC, between the objective/subjective scores, considered as a measure of prediction monotonicity [12].

The linear correlation coefficient (ideally equal to the unit), although not a direct measure of the mean error, is a common metric used to determine the accuracy of the prediction. For a set of N pairs (x_i,y_i) the linear correlation coefficient is defined as:

$$LCC = \frac{\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \overline{x})^2 \sum_{i=1}^{N}(y_i - \overline{y})^2}}, \quad (4)$$

where $\overline{x}$ and $\overline{y}$ are the mean values of the subsets x and y, which here represent MOS scores and objective scores.

Spearman rank-order correlation coefficient is defined as:

$$SROCC = \frac{\sum_{i=1}^{N}(\chi_i - \overline{\chi})(\gamma_i - \overline{\gamma})}{\sqrt{\sum_{i=1}^{N}(\chi_i - \overline{\chi})^2 \sum_{i=1}^{N}(\gamma_i - \overline{\gamma})^2}} = 1 - \frac{6 \cdot \sum_{i=1}^{N}(\chi_i - \gamma_i)^2}{N\left(N^2 - 1\right)}, \quad (5)$$

where χ_i and γ_i are x_i and y_i ranks, while $\overline{\chi}$ and $\overline{\gamma}$ are their mean values. This parameter compares the change between adjacent pairs of MOS values with a change between the corresponding objective values. As the SROCC only works with the rankings (order) of the data and ignores the relative distances between them, it is taken as a measure of correlation with less sensitivity and is typically used if the number of points (samples) is small. With the increase in the SROCC value, the monotonicity of the objective quality assessment measure (ideally, SROCC = 1) grows.

Table 2 summarises the performance of objective measures on subjective ReTRiEVED data, where metrics performance on individual degradation sets (sharing the same reference – videos produced from the same source sequence) are shown. This evaluation method takes advantage of subjects' ability to rank easily all videos produced from a single reference. Obviously, the best agreement is achieved between subjective and PSNR objective quality scores. Furthermore, the results show that the degree of subjective-objective agreement is the lowest for the test sequences obtained from the “Ducks takeoff” original.

Table 2
The degree of agreement between subjective and objective quality scores (source wise analysis).

Original sequence	LCC			SROCC		
	PSNR	SSIM	VQ^{AB}	PSNR	SSIM	VQ^{AB}
Crowd run	**0.949**	0.868	0.906	**0.899**	0.863	0.873
Ducks takeoff	**0.510**	0.367	0.398	**0.557**	0.373	0.367
Harbour	**0.900**	0.750	0.819	**0.853**	0.847	0.847
Ice	**0.872**	0.725	0.799	0.801	0.803	**0.804**
Park joy	**0.917**	0.798	0.830	**0.838**	0.757	0.759
Soccer	**0.832**	0.747	0.779	**0.783**	0.708	0.715
Running	**0.940**	0.815	0.899	**0.964**	0.940	0.958
Restaurant	**0.961**	0.835	0.912	**0.943**	0.941	0.941
Mean	**0.860**	0.738	0.793	**0.830**	0.779	0.783

Fig. 7 shows scatter plots of subjective (MOS) vs. objective quality estimates, with different degradation sets based on the same reference encoded with a differently coloured symbols (source-wise analysis). The same scatter plots are also shown in Fig. 8, but this time different degradation sets, based on the same type of degradation, are encoded using the same colour (degradation type analysis).

Figs. 7 and 8 illustrate a large spread of quality scores in 2D subjective–objective quality scores domain. This spread is least noticeable for Frame PSNR objective measure. In both cases, it is obvious that there are grouped quality estimates, most noticeably to the left of the main correlation line. These groups include points which refer to the test sequences obtained from “'Ducks takeoff” and “Park joy” source sequences (Fig. 7). Their underestimate of objective quality was down to temporal differences between the source and degraded videos.

Although all test sequences share the same temporal registration algorithm, these two sets show temporal discrepancies due to misalignments between source and test sequences after the registration. This problem is probably the result of delivered video contents. The results from **Table 2** then lead to the conclusion that Frame PSNR measure is more immune to temporal alignment problems than structural measures (see and compare objective performance for “Ducks takeoff” and “Park joy” sequences).

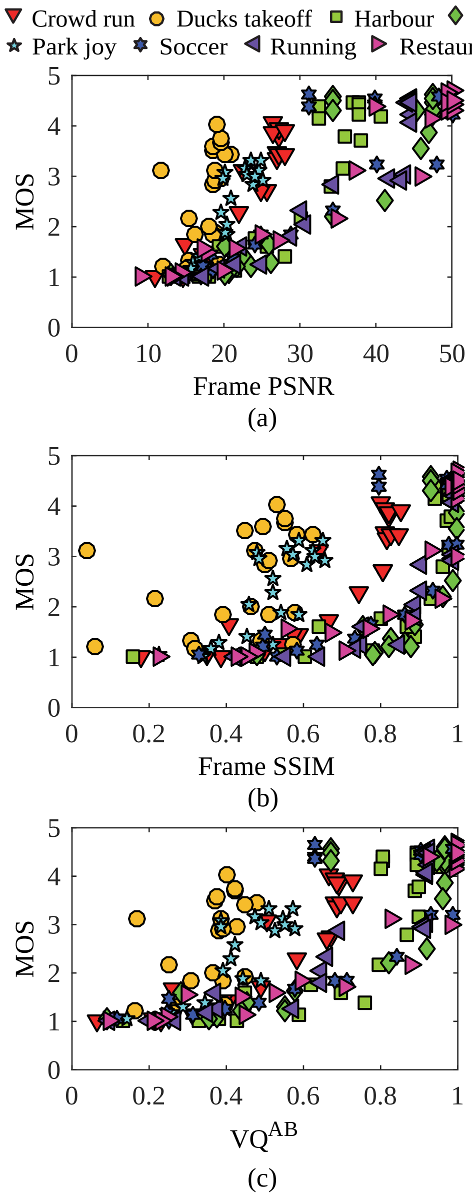


Fig. 7 – *Scatter plots of subjective vs. objective quality scores according to the source sequence.*

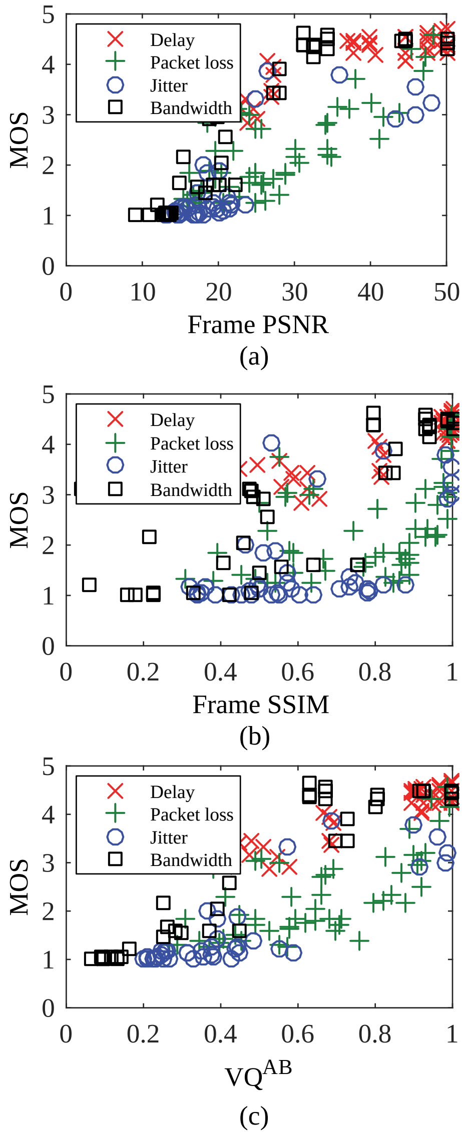


Fig. 8 – *Scatter plots of subjective vs. objective quality scores according to the type of degradation.*

Fig. 8 shows a significant grouping in the domain of subjective-objective quality scores for test sequences with jitter. The grouping is more evident at MOS (vertical) dimension, where test sequences receive quite unfavourable grades. As opposed to these test sequences, there are test sequences with delay which have grouping in the upper right part of the subjective-objective domain, i.e. the part that refers to the good and excellent quality of visual content. The distributions of the test sequences quality scores with the packet losses and limited bandwidth are more balanced.

Due to the detected problem of temporal registration, test sequences obtained from the “Ducks takeoff” and “Park joy” source sequences were not used in the analysis below.

Similar to the analysis shown in Fig. 5, there is an analysis on the impact of various types of degradations on PSNR objective quality values, Fig. 9. This measure was chosen because of better agreement with the subjective test results, compared to the other two, structural objective measures.

The results of PSNR are quite consistent with the results shown in Fig. 5. Fig. 9a indicates that the objective quality is not dependent upon the initial delay, but is dependent upon the content of video sequences. Results from Figs. 9b – 9d lead to the conclusion that mapping curves in the objective domain are consistent with the mapping curves of the subjective domain (Figs. 5b – 5d). The increases in jitter and the degree of packet loss rate have a negative impact on the objective quality values. The increase of jitter up to 3 ms leads to a dramatic decrease of objective values; from there on, they are approximately constant (Fig. 9b). The increase of packet loss rate up to 5 % results in a prompt decrease of objective quality values, after which they continue to decrease, although at a slower rate (Fig. 9c). The increase of transmission bandwidth up to 2 Mbps results in the linear increase of Frame PSNR values; after which they are constant.

Table 3 shows the degree of agreement between subjective and objective quality scores for the three subsets of ReTRiEVED dataset: subsets of test sequences with packet loss, jitter and bandwidth-limited transmission. It is obvious that SSIM objective measure shows worse performance in comparison to PSNR and VQ^{AB} measures.

Fig. 10 illustrates the ranks of various degradation types within the ReTRiEVED dataset, referring to the subjective and objective quality values (average values of all test sequences with the same type of degradation). Both subjective and objective quality scores, as expected, indicate that test sequences with delay have the best quality. Furthermore, both of the assessments have shown that sequences with jitter are of the poorest quality. Apart from that, it can be noted that all three objective measures overestimate the quality of test sequences with the packet loss, which they rank second, although they are ranked third according to subjective quality impressions. Packet losses cause short–term degradations in video sequences, both across space and time, unlike limited-bandwidth transmission which leads to quality degradation in the complete field of view and all frames. This explains the switch in ranks of the test sequences with the packet loss and the ones with bandwidth–limited transmission.

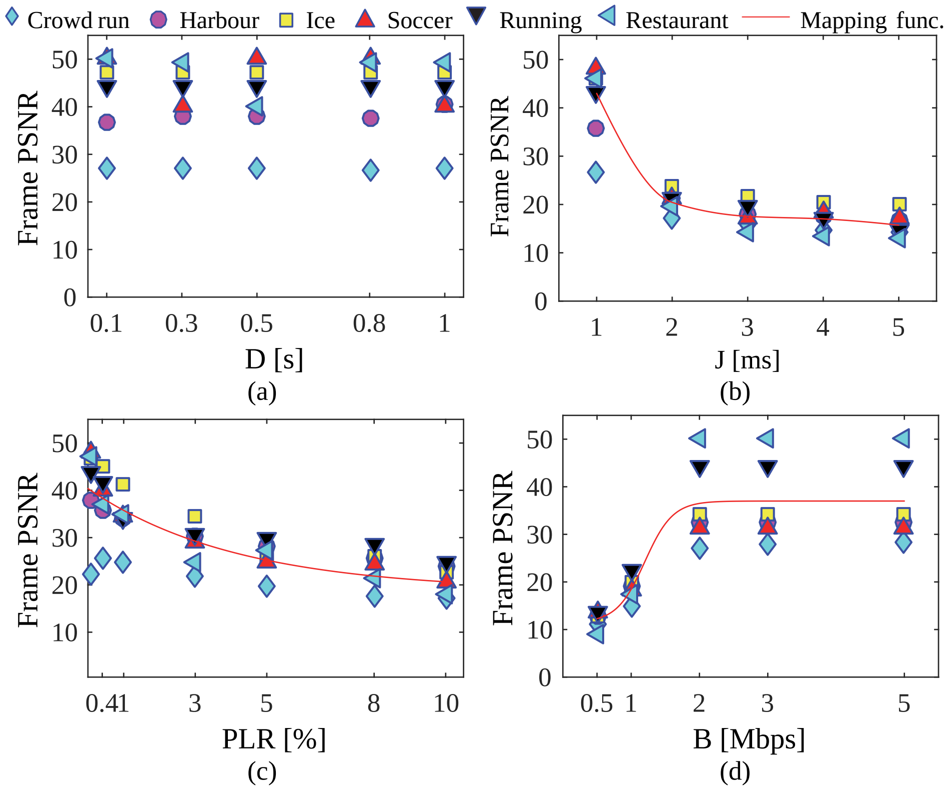


Fig. 9 – *The impact of various types of degradations on the objective quality: (a) the impact of delay on PSNR; (b) the impact of jitter on PSNR; (c) the impact of packet loss rate on PSNR; and (d) the impact of bandwidth on PSNR.*

Table 3
The degree of agreement between subjective and objective quality scores (degradation type analysis).

Degradation type	LCC			SROCC		
	PSNR	SSIM	VQ^{AB}	PSNR	SSIM	VQ^{AB}
PLR	**0.838**	0.602	0.780	0.779	0.727	**0.800**
Jitter	0.860	0.730	**0.886**	**0.787**	0.750	0.761
Bandwidth	0.892	0.895	**0.929**	**0.884**	0.815	0.777

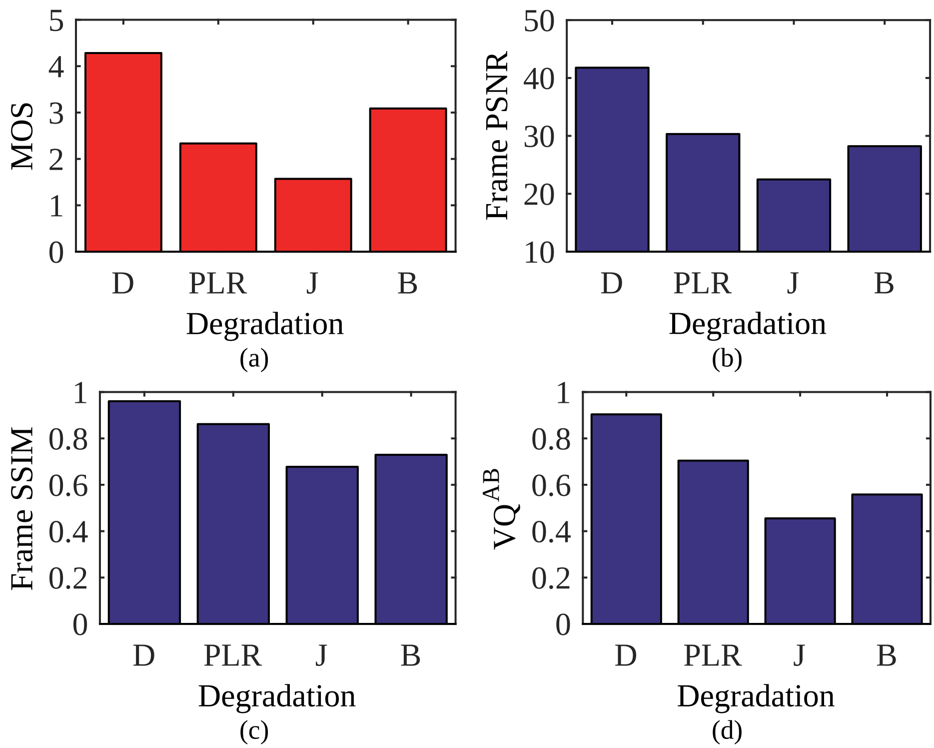


Fig. 10 – *Degradation types rankings according to subjective (a) and objective quality scores (b), (c) and (d).*

The performance of no-reference objective quality measures on the ReTRiEVED dataset, presented in [13], are worse in comparison to the performance of the objective measures referred to in this work. Thus, the obtained results can be used for the development of new objective video quality assessment measures in real applications.

5 Conclusion

Presented analysis of subjective test results on degraded video show that jitter, packet losses and bandwidth-limited transmission have a significant impact on subjective quality impressions while the initial delay does not affect the subjective quality. Additionally, it can be concluded that jitter has the most destructive effect. This result is based on the mapping functions of the subjective results. The spread of subjective (MOS) quality scores for the same value of degradation parameter indicates the need for further analysis of the impact of video content on the subjective perception of quality. For a small degree of degradation of video signals the influence of video content is higher, i.e. the spread of MOS scores around the interpolation function is greater. Therefore, the consideration of content of the video signal is of crucial importance for the development of the reliable QoE estimation measures.

Full-reference objective quality assessment measures achieved a relatively high degree of agreement with the results of subjective tests on subsets of sequences that originate from the same source sequence and on subsets of sequences with the same type of degradation. Moreover, the global degree of agreement is lower because objective measures overestimate the quality of sequences with packet losses. Therefore, in the development of objective video quality assessment special attention must be paid to spatial and temporal short–term signal degradations. Often criticized peak signal-to-noise ratio achieved better results than more complex structural similarity based measures. Mapping functions of objective PSNR scores are in good agreement with the interpolation curves of subjective quality scores. Further research will focus on no-reference and reduced-reference objective video quality assessment measures.

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