ON THE IMPROVEMENT OF NO-REFERENCE MEAN OPINION SCORE ESTIMATION ACCURACY BY FOLLOWING A FRAME-LEVEL REGRESSION APPROACH

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ABSTRACT

In order to estimate subjective video quality, we usually deal with a large number of features and a small sample set. Applying regression on complex datasets may lead to imprecise solutions due to possibly irrelevant or noisy features as well as the effect of overfitting. In this work, we propose a No-Reference (NR) method for the estimation of the quality of videos that are impaired by both compression artifacts and packet losses. Particularly, in an effort to establish a robust regression model that generalizes well to unknown data and to increase Mean Opinion Score (MOS) estimation accuracy, we propose a frame-level MOS estimation approach, where the MOS estimate of a sequence is obtained by averaging the per-frame MOS estimates, instead of performing regression directly at the sequence-level. Since it is impractical to obtain the actual per-frame MOS values through subjective experiments, we propose an objective metric able to do this task. Thus, our proposed NR method has the dual benefit of offering improved sequence-level MOS estimation accuracy, while giving an indication of the relative quality of each individual video frame.

***Index Terms*—** Estimation accuracy, frame-level quality estimation, MOS, objective metric, sequence-level quality estimation.

1. INTRODUCTION

Continuous technological advancements have enabled the proliferation of streaming video services and consequently, the matter of Video Quality Assessment (VQA) has become very popular. Since the goal of each video communication product is to satisfy user experience, subjective quality assessment is the most reliable way of evaluating its quality. Nonetheless, the carrying out of subjective tests faces many challenges. For example, a large number of viewers are required and the viewers are not always available or willing to rate a large variety of video sequences with different kinds of impairments. In addition, through subjective experiments we are unable to get instantaneous measurements of video quality due to many practical limitations. Thus, a single quality value for the whole video does not provide any information about the individual quality of the video frames, making it impossible to know which parts of the video have the greatest influence in forming the viewer's judgement.

An alternative approach to subjective VQA is to automatically get video quality scores, through the use of objective metrics [1, 2], where an ideal objective metric is able to provide quality scores that highly correlate with human ratings. In the literature, many works construct objective metrics through the use of various machine learning techniques, such as Partial Least Squares Regression (PLSR) [3], Neural Networks (NN) [4], Support Vector Machines (SVM) [5], and Support Vector Regression (SVR) [6]. Each considered regression model takes as input a number of quality-relevant features that account for different types of distortion and influence the accuracy of MOS estimations [7, 8]. Theoretically, the larger the number of features, the better the estimation power of the regression model. However, having a large number of features along with a possibly small number of observations (sample set) involves the risk of fitting the model to the noise of the training data, being unable to generalize well to unseen data (testing data). For this reason, a feature selection procedure often takes place before video quality estimation [9, 10].

In this work, we propose a No-Reference (NR) quality estimation method for videos that are impaired by both compression artifacts and packet losses. Our goal is two-fold: i) to improve the per-sequence MOS estimation accuracy through the development of a model which is robust and has a good generalization capability, and ii) to provide a reliable indicator for the quality of each frame of a video, offering an intuition about their individual contribution to the overall video quality score. In order to accomplish our goal, we develop a new metric, which is able to provide quality estimates for each individual frame. The requirement imposed on this metric is that its average MOS value over the whole video sequence should highly correlate with the actual MOS of the video sequence. The results produced by the developed metric play the role of the target variables in the regression procedure. Thus, we aim at the development of a NR method for the estimation of the MOS for each frame using features of the received video bitstream, which, when averaged over the whole video sequence, give an accurate estimation of the MOS of the video sequence.

The works presented in [11, 12] elaborated on the concept of considering frame quality measurements and measurements over small parts of video sequences that guide the overall video quality rating. However, the goal of both [11, 12] is different from the one of the current paper. In [11] a NR objective metric that provides two video quality scores per second so as to align with the subjective results of a Single Stimulus Continuous Quality Evaluation (SSCQE) method [13] was introduced, and in [12] the authors applied a fusion mechanism in order to integrate the scores from some video intervals into a final one, increasing in this way the correlation with the MOS.

The rest of the article is organized as follows: Section 2 presents the objective metric that offers the ground truth of frame video quality. Section 3 summarizes the extracted features that are used for the MOS estimation procedure. Our approach for estimating MOS at the frame-level is analyzed in Section 4 along with experimental results and a comparison with regression applied directly at the sequence-level and other recently proposed competing methods. Last, in Section 5 conclusions are drawn.

2. FRAME QUALITY GROUND TRUTH

In order to estimate the MOS per frame, it is necessary to obtain the ground truth for each frame, MOS_{fr}. For this purpose, we propose here a mathematical tool to help us achieve our goal. Although we use the term "MOS per frame", it is clear that ground truth cannot be obtained using subjective tests where the viewers look at the whole video sequence. Thus, the proposed MOS per frame can be seen as a Full-Reference (FR) objective metric, which produces quality scores for each individual frame. As mentioned previously, it is important that the average MOS value over all frames of a sequence, $\overline{\mathrm{MOS}_{fr}}$, highly correlates with the actual MOS for each sequence, MOS_s, obtained via subjective tests.

The research conducted in [14] proved that an exponential function can map Peak Signal to Noise Ratio (PSNR) to MOS with high accuracy, considering the temporal and spatial activity levels of the video sequence in question. This function is given by:

$$\mathrm{MOS}_s = \exp\left(\frac{\mathrm{PSNR}_s - a}{b}\right) - 1 \qquad (1)$$

where the parameters a and b represent the vertical shift and the steepness of the curve, and MOS_s, PSNR_s correspond to the MOS and PSNR, respectively, for each sequence.

In this paper, we propose to use Eq. (1) at the frame level in order to obtain the ground truth for the MOS per frame. For our experiments, we employ the database of [15] for 4 Common Intermediate Format (4CIF) resolution sequences (704 $\times$ 576 pixels). Our test material comprises the "Ice", "Harbour", "Soccer", "CrowdRun", "DucksTakeOff" and "ParkJoy" sequences of 238, 298, 298, 250, 250 and 250 frames, respectively; the former three sequences are at 30 frames per second (fps) and the latter three at 25 fps. The Group Of Pictures (GOP) structure is IBBP with a GOP size of 16 frames. The sources are encoded using the JM 14.2 version of H.264/AVC reference software using the High profile, where a full row of MacroBlocks (MBs) is coded as a separate slice and each of the sequences is corrupted with a Packet Loss Rate (PLR) of $0.1\%, 0.4\%, 1\%, 3\%$, 5% and 10%, for two channel realizations. Thus, our dataset consists of 72 distorted versions of the six original video sequences (6 original sequences $\times$ 6 PLRs $\times$ 2 channel realizations). In addition, in [15] subjective MOS results from the Ecole Polytechnique Fédérale de Lausanne (EPFL) and Politecnico di Milano (PoliMi) are also provided. It is to be noted that, in this paper, we conducted experiments using both EPFL and PoliMi MOS values and a very similar performance was observed. Due to this, and in order to save space, we present results using only the PoliMi MOS.

Since the metric proposed in [14] was only tested on CIF resolution sequences with a frame rate of 30 fps, it was necessary to verify if Eq. (1) also fits well to 4CIF resolution sequences at both 30 fps and 25 fps. Experiments carried out on each separate sequence showed that the coefficient of determination R^2, which is an indicator of how well the observed outcomes are replicated by the model, was always greater than 0.92. Based on these results, it is clear that the exponential shape of Eq. (1) accurately describes the MOS-PSNR relationship also for 4CIF sequences.

In this direction, for each of the 72 video sequences, we calculate their PSNR values, PSNR_s (for the whole sequence), and using the MOS values of [15], MOS_s, we apply Ordinary Least-Squares (OLS) optimization in order to solve for the parameters a and b of Eq. (1). Afterwards, we calculate the PSNR values for each frame of all considered 4CIF sequences, PSNR_{fr}, and next we compute MOS_{fr} by applying Eq. (1). In other words, we use Eq. (1) for each frame (instead of the whole sequence as originally proposed in [14]) in order to obtain the ground truth of the MOS per frame. For the validation of the quality of the obtained values, we average the per-frame MOS values to obtain a representative value for each sequence, $\overline{\mathrm{MOS}_{fr}}$, and check for correlation with the corresponding measured values, MOS_s.

MOS results obtained using subjective tests are typically compressed at the ends of the 5-point rating scale [15]. In order to impose the same behavior to our estimates, we apply a non-linear mapping on the $\overline{\mathrm{MOS}_{fr}}$ values, before computing any of the performance metrics discussed later. Specifically, we use the cubic polynomial function given by [16]:

$$\overline{\mathrm{MOS}'_{fr}} = a_1\,\overline{\mathrm{MOS}_{fr}}^3 + a_2\,\overline{\mathrm{MOS}_{fr}}^2 + a_3\,\overline{\mathrm{MOS}_{fr}} + a_4 \qquad (2)$$

which is found to perform well empirically. The weights a_1, a_2, a_3 and the constant a_4 are calculated by fitting the function to the data $(\overline{\mathrm{MOS}_{fr}}, \mathrm{MOS}_s)$ with the goal of maximizing their correlation.

The relationship between $\overline{\mathrm{MOS}'_{fr}}$ and MOS_s is given by the scatter plot of Fig. 1, for all 4CIF sequences. From this figure, we confirm a nearly perfect linear relationship in terms of the Pearson Correlation Coefficient (PCC) [16], which is equal to 0.99. It is to be noted that PCC = 1 indicates a perfect positive correlation between the measured and estimated data.

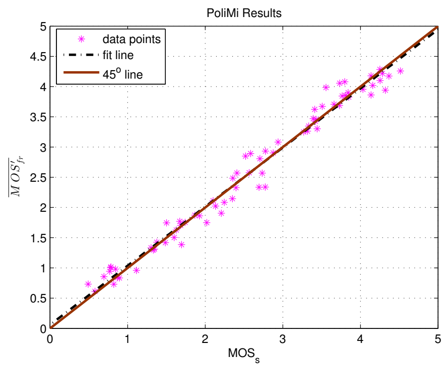

Fig. 1: Correlation results.

The estimated a and b parameters as well as the PCC for each separate sequence are depicted in Table 1. As we can see from this table, if we apply the parameters a and b to Eq. (1), the subjective results can be estimated with a nearly perfect precision.

Table 1: Estimated a and b values.

	PoliMi MOS					
	CrowdRun	DucksTakeOff	Harbour	Ice	ParkJoy	Soccer
a	15.62	15.35	12.08	16.55	15.39	15.97
b	9.99	9.06	14.26	13.44	9.79	12.16
PCC	0.98	1.00	0.99	0.98	0.98	1.00

More light about the efficiency of the aforementioned FR metric is shed by the results presented on Table 2. A comparison of the employed metric used for taking per-frame MOS quality values with the state-of-the-art Perceptual Evaluation of Video Quality (PEVQ) [17] and Video Quality Metric (VQM) [18] reveals that although all of these metrics correlate well with MOS, the metric proposed in this article is even more efficient in terms of PCC [16], Spearman Rank Order Correlation Coefficient (SROCC) [19] and RMSE [16]. Thus, our experimental results verify the suitability of the proposed MOS per frame metric for estimating the actual MOS per sequence.

Table 2: FR objective metrics comparison.

	Proposed	PEVQ	VQM
PCC	$\mathbf{0.99}$	0.96	0.96
SROCC	$\mathbf{0.99}$	0.97	0.96
RMSE	$\mathbf{0.18}$	0.38	0.54

3. FEATURES CAPTURING VIDEO DISTORTION

Except for the ground truth, which is required in supervised learning regression problems and plays the role of the target variable that needs to be estimated, a design matrix that includes the values for the explanatory variables is also assumed so as to be taken as input to a considered regression model. In this work, we use a large number of bitstream-based features, 45 in total, that are expected to affect perceptual video quality. The specific features account for compression artifacts and packet-loss impairments and, based on how they relate to the different types of distortion, can be characterized as features related to video content characteristics, signal features, error features, motion features and features related to the effectiveness of the error concealment technique. Particularly, they are described as follows:

- **Intra[%]** is the percentage of I coded MBs in a slice.
- **I4** $\times$ **4inIslice[%]** is the percentage of MBs of size 4×4 in an I slice.
- **I16** $\times$ **16inIslice[%]** is the percentage of MBs of size 16×16 in an I slice.
- **IinPslice[%]** is the percentage of I coded MBs in a P slice.
- **P[%]** is the percentage of P coded MBs in a slice.
- **P_Skip[%]** is the percentage of MBs coded as P_Skip in a slice.
- **P16** $\times$ **16[%]** is the percentage of P MBs coded with no sub-partition of MBs in a slice.
- **P8** $\times$ **16[%]** is the percentage of P MBs coded with 8×16 and 16×8 partition of MBs in a slice.
- **P8** $\times$ **8[%]** is the percentage of P MBs coded with 8×8 partition of MBs in a slice.
- **P8** $\times$ **8_Sub[%]** is the percentage of P MBs coded with 8×8 in a sub-partition of MBs in a slice.
- **P4** $\times$ **8[%]** is the percentage of P MBs coded with 4×8 and 8×4 sub-partition of MBs in a slice.
- **P4** $\times$ **4[%]** is the percentage of P MBs coded with 4×4 sub-partition of MBs in a slice.
- **B_modes** correspond to the same features as referred above from feature **P[%]** to feature **P4** $\times$ **4[%]**, but for B MBs.
- **mvx_dif**, **mvy_dif** are the average measures of motion vector difference values for x and y direction in a slice.
- **mvx_av**, **mvy_av** are the average measures of motion vector values for x and y direction in a slice.
- **mv_zero[%]** is the percentage of motion vector values equal to zero for x and y direction in a slice.
- **mv_zero_dif[%]** is the percentage of motion vector difference values equal to zero in a slice.
- **Motion Intensity_1** equals $\sum_{i=1}^{N} \sqrt{mvx\_av_i^2 + mvy\_av_i^2}$, where N is the total number of MBs in a slice.
- **Motion Intensity_2** equals $\sqrt{mvx\_av^2 + mvy\_av^2}$.
- **mvx_abs**, **mvy_abs** are the average measures of absolute motion vector values for x and y direction in a slice.
- **Motion Intensity_3** equals $\sum_{i=1}^{N} \sqrt{mvx\_abs_i^2 + mvy\_abs_i^2}$.
- **Motion Intensity_4** equals $\sqrt{mvx\_abs^2 + mvy\_abs^2}$.
- **DistToRef** is the distance in frames between the current frame and the reference frame used for concealment.
- **FarConceal** is a boolean factor, which is true if $|\text{DistToRef}| \geq 3$.
- **LostSlicesInFrame** is the number of lost slices in a frame.
- **Height** is the vertical location of a lost slice within a frame.
- **TMDR** is the number of frames affected by a lost slice.
- **SpatialExtend** is the number of consecutive lost slices in a frame.
- **SXTNT2** is a boolean variable, which is true if SpatialExtend=2.
- **SXTNTFrame** is a boolean variable, which is true if all slices of a frame are lost.
- **Error1Frame** is a boolean variable, which is true if TMDR=1.
- **MaxResEngy**, **MeanResEngy** are the maximum and mean residual energy over all the MBs of a slice.
- **NotStill** is a boolean variable, which is true if the magnitude of a slice (as it is computed from feature **Motion Intensity_2**) is over 1/10 of the highest magnitude value of all sequences.
- **HighMot** is a boolean variable, which is true if the magnitude of a slice is over 8/10 of the highest magnitude value of all sequences.

Some of the aforementioned features are related to the occurrence of a packet loss and thus, they are computed at the slice level, while the features that are related to motion vectors are computed at the MB level. For our frame-level regression problem, all feature observations that are calculated at the MB- or slice-level are averaged to obtain representative values for each frame. On the contrary, for the regression problem at the sequence-level, the frame-level feature observations are averaged further to get a feature value for each separate sequence.

4. MOS ESTIMATION PROCEDURE

Having collected the feature observations as well as the MOS ground truth, we proceed with applying regression. For the frame-level case, we construct a regression model that generates per-frame MOS estimates, EMOS_{fr}, which will be next averaged to provide an overall MOS value for each sequence, $\overline{\text{EMOS}_{fr}}$. For comparison purposes, we also develop a regression model that operates directly in the sequence-level domain and produces per-sequence MOS estimates, EMOS_s. Our frame-level dataset includes 19008 feature observations (one feature value for each frame) and the sequence-level dataset consists of 72 feature observations (one feature value for each sequence). Next, we apply *Ridge regression* [20, 21] in both the frame- and sequence-level domains.

Table 3: Performance statistics.

	Raw dataset		Processed dataset		Related works	
	Sequence-level	Frame-level	Sequence-level	Frame-level	G.1070E [7]	$\mathrm{SLR_{IP}}$ + $\mathrm{SLR_{B}}$ [8]
PCC	0.87	0.96	0.96	**0.97**	0.93	0.96
SROCC	0.85	0.96	0.96	**0.97**	0.91	–
RMSE	0.58	0.34	0.31	**0.28**	0.37	0.34

Ridge is an extension of the OLS regression method and is able to improve the OLS estimates by allowing a little bias in order to reduce the variance of the estimated values. It solves the problem:

$$\min_{w}\left(\frac{1}{2}\sum_{i=1}^{n}(y_i - w^\top\phi(x_i))^2 + \frac{\lambda}{2}\|w\|^2\right) \tag{3}$$

where y includes the measured quality values for all n observations and x_i includes the values for all features for a specific observation i. The parameter $\lambda \geq 0$ is a regularization parameter, which shrinks regression coefficient values towards zero. For $\lambda = 0$, no shrinkage is performed and the solution of the OLS is obtained, while for larger λ values, the closer to zero the regression coefficient estimates. In our experiments, we set $\lambda = 10^{-5}$ in the regression models of both domains. Therefore, Ridge tradeoffs the sum of squared errors (first term of Eq. (3)) and the penalty (second term of Eq. (3)).

The column "Raw dataset" of Table 3 presents the PCC, SROCC and RMSE statistics, when regression is applied in both the frame- and sequence-level domains, by employing all 45 features extracted from the bitstreams. For the frame-level case, the MOS estimates for each frame obtained from Ridge are averaged to obtain a MOS value for each video sequence, $\overline{\mathrm{EMOS}_{fr}}$ and next, we compare these results with the actual sequence-level MOS values, MOS_s. For the sequence-level case, the actual MOS values, MOS_s, are compared with the MOS values obtained from Ridge, EMOS_s. Examining the "Raw dataset" results of Table 3, it is clear that regression on the frame-level dataset guarantees exceptionally good performance statistics that are definitely better than the statistics achieved by performing regression on the sequence-level dataset.

In an effort to enhance the strength of the sequence-level regression model in making precise estimations, we apply *Stepwise regression* [22] so as to elaborate on the extracted features and keep only the most beneficial of them as well as to make use of their most favorable pairwise interactions. The specific method starts with an initial dataset and then compares the explanatory power of incrementally larger or smaller datasets. Algorithm 1 below summarizes the basic idea of this methodology.

Algorithm 1 Stepwise Regression

```
Initialize: No predictors in the model.
1: repeat
2:     if F-test p-value ≤ 0.05 then  // predictors not in the model
3:         Add the predictor with the smallest p-value;
4:     else if F-test p-value ≥ 0.10 then  // predictors in the model
5:         Remove the predictor with the largest p-value;
6:     else
7:         return ;
8:     end if
9: until return
```

This procedure is performed separately in the sequence- and frame-level domains, and thus, some of our initial features are eliminated from each corresponding dataset. At the same time, pairwise feature interactions are added in order to ameliorate the precision of the estimations. After conducting Stepwise regression, we end up with a sequence-level dataset of dimension 72×26 and a frame-level dataset of dimension 19008×95. This means that the number of features is significantly reduced in the sequence-level dataset and considerably increased in the frame-level dataset. Due to space limitations, we do not show in this paper the selected features as well as their pairwise interactions utilized by the regression models for each case.

On the processed sequence-level and frame-level datasets, we again apply Ridge regression (Eq. (3)) to obtain the new MOS estimates. The column "Processed dataset" of Table 3 presents the performance statistics, when regression is performed by employing only the features and their interactions as indicated after applying Alg. 1 in both the sequence- and frame-level domains. The provided results reinforce our claim that a more stable model is achieved when regression is applied at the frame-level, which offers more precise MOS estimations compared to the model built at the sequence-level. Interestingly, only a minor improvement is observed compared to the already high frame-level performance statistics of the raw dataset. Regarding the sequence-level case, the correlation measures as well as the RMSE are considerably improved in this case, compared to the case of regression on the raw dataset.

Continuing, Table 3 not only includes the comparison of our proposed regression model that operates in the frame-level domain with the regression procedure performed directly in the sequence-level domain, but also presents comparison with recent related works [7, 8] (column "Related works") that develop NR video quality metrics, based on a similar rationale of using perceptually-driven features. Both [7] and [8] use the database of [15], and estimate MOS directly for each sequence. An overall look at the results of this table makes clear that our approach of exploiting a much larger number of feature observations as well as the concept of making estimations at the frame level lead to very good performance statistics that outperform the results of competing approaches.

5. CONCLUSIONS

In this paper, we proposed a novel No-Reference method for the quality estimation of videos that are impaired by both compression artifacts and packet losses. We introduced a Full-Reference metric, which is able to provide the quality ground truth for each frame and next, we developed a regression method for its estimation, using a number of features extracted from the received video bitsteam. The MOS of the video sequence was estimated as the average of the estimated MOS per frame values. The presented experimental results show that the proposed frame-domain approach provides more accurate estimates of the actual MOS of a video sequence than a sequence-domain approach, and also outperforms recently-proposed competing methods. Moreover, the proposed method offers the additional benefit of providing an indication of the quality of each individual frame, something that sequence-domain approaches cannot do.

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