Disentangling Aesthetic and Technical Effects in Video Quality Assessment for User Generated Content

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Abstract

User-generated-content (UGC) videos have dominated the Internet during recent years. While it is well-recognized that the perceptual quality of these videos can be affected by diverse factors, few existing methods explicitly explore the effects of different factors in video quality assessment (VQA) for UGC videos, i.e., the UGC-VQA problem. In this work, we make the first attempt to disentangle the effects of aesthetic quality issues and technical quality issues risen by the complicated video generation processes in the UGC-VQA problem. To overcome the absence of respective supervisions during disentanglement, we propose the Limited View Biased Supervisions (LVBS) scheme where two separate evaluators are trained with decomposed views specifically designed for each issue. Composed of an Aesthetic Quality Evaluator (AQE) and a Technical Quality Evaluator (TQE) under the LVBS scheme, the proposed Disentangled Objective Video Quality Evaluator (DOVER) reach excellent performance (0.91 SRCC for KoNViD-1k, 0.89 SRCC for LSVQ, 0.88 SRCC for YouTube-UGC) in the UGC-VQA problem. More importantly, our blind subjective studies prove that the separate evaluators in DOVER can effectively match human perception on respective disentangled quality issues. Codes and demos are released in https://github.com/teowu/dover.

1. Introduction

Increasing numbers of videos are produced every day by a huge diversity of users and occupy a significant amount of the data transmitted on the Internet nowadays. These user-generated-content (UGC) videos are of diverse quality, which arouses attention to the video quality assessment algorithms for UGC videos, i.e., UGC-VQA problem [1]. While recent studies are collecting subjective quality scores for UGC videos [2–6] and objectively predicting these subjective quality scores [7–11], the effects leading to the various quality scores of UGC videos is still unclear.

In general, both aesthetic and technical quality issues can occur in a UGC video during its generation processes, as depicted in Fig. 1. For aesthetic quality issues [12], many studies [13–16] have demonstrated that the visual aesthetic experience of a video is relevant to whether professional photography techniques are appropriately used, during the processes of target content selection and viewpoint organization. For instance, targeting unappealing or meaningless objects or organizing objects in a chaotic way would severely degrade the perceived aesthetic experience (see Fig. 1(a)) with non-negligible impacts on the perceptual quality of UGC videos [6, 17]. In contrast to the aesthetic quality issues, the technical quality issues (e.g., noises, blurs, compression artifacts, etc) in UGC videos are usually caused by machine-related processes, such as video capturing [18–20], compression/transmission [21–24], and post-processing [25, 26], as illustrated in Fig. 1(b). In these processes, various machine-caused technical flaws [27] are present in UGC videos, which are widely acknowledged to be crucial to the perception of UGC video quality [5, 8, 28]. While both quality issues are well-recognized to occur in UGC videos, most existing VQA methods only consider one aspect between them [5, 6, 8, 11, 17, 29], or have not yet explicitly model their effects [10, 30, 31] on UGC-VQA.

In this paper, we make the first attempt to disentangle the two aforementioned issues in the UGC-VQA problem, with the goal of investigating the separate effects of aesthetic and technical quality issues in UGC-VQA and thereby learning more specific representations that reflect quality perception. However, due to the absence of separate subjective labels for the two effects in existing VQA databases [2–5, 18, 19], the disentanglement between them is practically difficult.

To overcome this difficulty, we analyze the causes of the two issues and notice that they are related to different factors: the aesthetic quality is more concerned with the semantics and composition of visual objects [32], whereas the technical quality is sensitive to low-level components such as blurs, noises, and artifacts [19]. Inspired by this insight, we propose a View Decomposition strategy, which decomposes the original video into two limited views, each
of which is mainly sensitive to the factors associated with a specific quality issue. Two evaluators are then built on the decomposed views and supervised from overall quality scores. With the inductive biases from the limited views, each evaluator mainly learns the effects of its respective issues, named as Limited View Biased Supervisions (LVBS).

Specifically, we propose the Aesthetic Quality Evaluator (AQE) on Aesthetic-specific Views, which are designed as spatially downsampled and temporally sparse sampled videos to eliminate the majority of technical quality issues but can effectively distinguish the semantics and composition of objects that occur in videos. Through multi-scale learning, the AQE is further regularized to reduce the effects of technical issues and focus on aesthetics. Similarly, we propose the Technical Quality Evaluator (TQE) on Technical-specific Views, which are based on the recently-proposed fragments [11]. The fragments are stitched from uniformly-sampled random patches and are proven to cover technical quality issues. Fragments also discard most semantics and severely disrupt the aesthetic information in videos. The randomness of the remained contents in fragments further disrupts aesthetics and serves as implicit regularization for the TQE. The two evaluators are learned under the LVBS scheme and can be fused for overall quality evaluation of UGC videos, composing the proposed Disentangled Objective Video Quality Evaluator (DOVER).

In general, our contributions are four-fold:
1) We make the first attempt to disentangle aesthetic and technical effects in UGC-VQA, via the proposed Limited View Biased Supervisions (LVBS) scheme.
2) Under the LVBS scheme, we propose the DOVER as the first implementation of decoupling in UGC-VQA, with only overall quality scores as supervisions.
3) The DOVER effectively learns separate aesthetic and technical quality in concordance with human opinions, as validated by blind subjective studies.
4) After fusion, the DOVER achieves state-of-the-arts on overall quality prediction in UGC-VQA, under both score-level and representation-level fusion settings.

2. Related Works

2.1. Subjective Studies on UGC-VQA

Unlike traditional VQA datasets [18, 19, 23, 24], UGC-VQA datasets directly collect from real-world videos. The LIVE-VQC [4] dataset consists of 585 videos from a variety of smartphone photography without compression. KoNVid-1k [2] and LSVQ [5] are collected from social media video database YFCC-100M [33], while YouTube-UGC [34] is also collected from social media [3]. Specifically, it contains a large proportion of videos of Animation, Gaming or Lyric Videos, which are novel content types to be evaluated in the VQA task. In general, different from the traditional VQA task, in UGC-VQA, each video has its own target content and view (or object organization) and can be produced by either professional or non-professional users [27, 35]. Moreover, the subjective rating processes for UGC-VQA datasets are conducted by crowdsourced unprofessional raters [36]. Due to the relatively diverse collection and annotation processes, the quality scores for UGC videos are entangling multiple factors and hard to be interpreted.

2.2. Objective Studies on UGC-VQA

Classical VQA methods [37–41] employ handcrafted features to evaluate video quality. Some methods [42–45] hypothesize that they can predict quality scores from statistical hypotheses without regression from any subjective labels. More recent methods [1, 8, 46] choose to first handcraft quality-sensitive features and then regress them to subjective mean opinion scores (MOS), in order to better match human perception. Nevertheless, classical methods are neither aware of contents nor able to distinguish aesthetics, and are thus usually less accurate on UGC-VQA datasets.

Recently, deep VQA methods [6, 10, 11, 17, 30, 47–52] are becoming predominant in the UGC-VQA problem, with some methods starting to consider either aesthetic or technical issues in this problem. Some methods consider aesthetic quality issues: VSFA [17] conducts subjective studies to demonstrate attractive objects in VQA
receive higher subjective ratings. Therefore, it uses the semantic-aware features extracted by pre-trained ResNet-50 [53] from ImageNet-1k dataset [54] and adopts Gate Recurrent Unit (GRU) [55] for quality regression. MLSP-FF [6], reaches good performance on UGC-VQA databases by applying their aesthetic assessment approach, MLSP-IAA [14]. Other methods are focusing on technical distortions by transferring from frame-wise pre-training [5, 9, 31] on IQA databases [56, 57], or designing technical-sensitive inputs [11, 28]. Still, few methods consider both issues or try to disentangle their effects in the UGC-VQA problem.

2.3. Disentangled Representation Learning

To separate different factors and learn more robust and explainable representations, efforts on disentangled representation learning usually rely on inductive biases [58, 59] that help the model to focus on specific factors. This could be achieved by inductive biases on data [60–62] by manipulating the inputs, or on learning objectives [63–65] by setting several regularization objectives for the output representations. Inspired by these studies, we design the Limited View Biased Supervision (LVBS) scheme to learn disentangled aesthetic and technical effects in UGC-VQA.

3. Our Approach: the DOVER

Observing that UGC-VQA is affected by both aesthetic and technical issues (Sec. 3.1), we design the Limited View Biased Supervisions (LVBS, Sec. 3.2) scheme to disentangle their effects, and propose the Disentangled Objective Video Quality Evaluator (DOVER, Fig. 2), in which the separate aesthetic and technical evaluators are discussed in Sec. 3.3 and Sec. 3.4. Finally, we introduce the fusion strategies for overall video quality prediction in Sec. 3.5.

3.1. Observation: Entangled Nature of UGC-VQA

Traditionally, aesthetic and technical quality assessments have long been studied separately [66]. In aesthetic evaluation [16, 67, 68], photographs are usually taken by technically professional equipment (e.g., DSLR), and their quality highly depends on the semantics of objects in photos and whether they are professionally organized (e.g., rule of thirds, symmetry). In contrast, images or videos collected for technical quality assessment [18, 19, 24] are usually with various shooting equipment or processing algorithms. Different from traditional settings with distinct discrimination between them, aesthetic quality issues (Fig. 1(a)) and technical quality issues (Fig. 1(b)) are both prevalent [6, 17, 27] in the acquisition of UGC videos, and affect their quality perception. In Fig. 3, we also notice that extremely low-quality videos (lowest 5% scores) are with bad aesthetics or/and bad technical quality.
3.2. Limited View Biased Supervision (LVBS)

Aesthetic and technical quality issues are associated with different factors. Specifically, aesthetic perceptions are typically related to meaningfulness, organization, composition of objects [13, 16, 32], which belong to high-level semantic visual perceptions. In contrast, the technical quality is largely affected by low-level visual distortions, e.g., blur, noise, compression artifacts, flicker [5, 11, 57, 69, 70]. Moreover, theoretical studies [58, 59] and extensive practices [60–63] on disentangled representation learning have demonstrated that disentanglement on different factors can be achieved by including respective inductive biases for different factors either on input data or learning objectives.

Disentanglement with View Decomposition. Inspired by the aforementioned studies, we propose the View Decomposition strategy to impose input-level inductive biases for aesthetic and technical issues. First, we decompose the original videos into two specific views: Aesthetic-specific Views (\(S_A\)), which are sensitive to aesthetic-related perception but with reduced sensitivity to low-level technical distortions; and Technical-specific Views (\(S_T\)), which are sensitive to technical distortions but corrupt the aesthetics of videos. Based on the decomposed views, we build an aesthetic quality evaluator (AQE, denoted as \(M_A\)) on \(S_A\), and a technical quality evaluator (TQE, denoted as \(M_T\)) on \(S_T\) to separately learn the aesthetic quality prediction \(Q_{\text{pred},A}\) and technical quality prediction \(Q_{\text{pred},T}\):

\[
Q_{\text{pred},A} = M_A(S_A); Q_{\text{pred},T} = M_T(S_T) \tag{1}
\]

Supervision with Overall Scores. The decomposed views with inductive biases ensure that each separate evaluation (\(Q_{\text{pred},A}\) or \(Q_{\text{pred},T}\)) can mostly relate to one aspect of quality issues. Therefore, when we separately supervise the two evaluators with the overall quality scores (MOS), each evaluator shall be able to learn the effects of its respective quality issues on the overall quality. Thus, we propose the Limited View Biased Supervisions (LVBS) by minimizing the distance (\(L_{\text{Sup}}\)) between separate predictions and MOS in both evaluators (\(\Theta(M)\) denotes parameters in \(M\)):

\[
\min_{\Theta(M_A)} L_{\text{Sup}}(Q_{\text{pred},A}, \text{MOS}) \tag{2}
\]

\[
\min_{\Theta(M_T)} L_{\text{Sup}}(Q_{\text{pred},T}, \text{MOS}) \tag{3}
\]

The details for the loss \(L_{\text{Sup}}\) are in Appendix Sec. E.1. Moreover, we introduce regularization strategies as further inductive biases on the learning objectives. The designs on specific views and regularization are discussed as follows.

3.3. Aesthetic Quality Evaluator (AQE)

To preserve aesthetic-related perception and remove the technical effects to the greatest extent in the AQE, we elaborate the Aesthetic-specific Views (\(S_A\)) and further introduce additional regularization objectives.

![Figure 4. Several examples for (a) Aesthetic-specific Views (\(S_A\)) and (b) Technical-specific Views (\(S_T\)) in the View Decomposition strategy. Both views effectively exclude perception on the other type of quality issues.](image)

Aesthetic-specific Views. As aesthetic perception is related to meaningfulness of objects and composition among them, we need to retain the semantic information (i.e. majority of objects are still recognizable) and contextual information (i.e. all objects in their original positions) in the Aesthetic-specific Views. Following the principle, we obtain Aesthetic-specific Views (see Fig. 4(a)) through spatial down-sampling\(^1\) [72] and temporal sparse frame sampling [73] which preserves the semantics and compositions of original videos. The down-sampling strategies are widely applied in many existing state-of-the-art aesthetic assessment methods [13, 15, 32, 71, 74], further proving that they are able to preserve aesthetic information in visual contents. Moreover, the two strategies significantly reduce the sensitivity [1, 8, 37, 45] on technical quality issues such as blur, noise, artifacts (via spatial down-sampling), shaking, flicker (via temporal sparse sampling), so as to focus on aesthetics.

Regularization: Multi-scale Learning. To further reduce the technical effects in the AQE, we propose to over-downsample the videos into \(S_A\) with less texture-related technical quality information (but still keeps similar aesthetics, see Fig. 2(b) middle). The \(S_A\) and \(S_A\) are both fed into training, so as to regularize the AQE to predict quality with less consideration on technical quality issues.

In addition, existing study [75] suggests that feature dissimilarity among different scales is related to technical quality. As the dissimilarity is also noticed in our training process (Appendix Sec. C.1), we impose the Cross-scale Restraint (\(L_{\text{CR}}\), Fig. 2(d)) to further eliminate the technical influences by encouraging the feature similarity of \(S_A\) and \(S_A\), and the objective functions for AQE are as follows:

\[
\min_{\Theta(M_A)} L_{\text{Sup}}(M_A(S_A), \text{MOS}) + \lambda_{\text{CR}} L_{\text{CR}} + L_{\text{Sup}}(M_A(S_A), \text{MOS}) \tag{4}
\]

where \(L_{\text{CR}} = 1 - \frac{F_A \cdot F_{A_A}}{\|F_A\| \cdot \|F_{A_A}\|}
\]

\(^1\)We notice that down-sampling changes the aspect ratio. However, our experiments show that changing the aspect ratio in the AQE does not affect the overall accuracy of DOVER, similar to previous conclusions [15, 71].
where $F_A$ and $F_{A\parallel}$ are output features for $S_A$ and $S_{A\parallel}$.

### 3.4. Technical Quality Evaluator (TQE)

In the TQE, we would like to keep the technical distortions but obfuscate the aesthetic information of videos so as to predominantly focus on technical quality issues. Thus, we introduce the Technical-specific Views ($S_T$) and respective implicit regularization strategies as follows.

**Technical-specific Views.** We introduce fragments [11] (see in Fig. 4(b)) as Technical-specific Views ($S_T$) for the TQE. The fragments are composed of randomly cropped raw patches stitched together to retain the technical distortions. Moreover, it discarded most of semantic-level content and shuffled the positional relations of the remaining, therefore severely corrupting the aesthetic information in videos. Temporally, we also apply continuous frame sampling for $S_T$ to retain temporal technical distortions.

**Implicit Regularization.** As illustrated in Fig. 2(b), a fixed original video can be either randomly sampled into $S_T$, or a different $S_{\overline{T}}$, with different objects remained. Moreover, the positional relations in original videos among the patches are different between $S_T$ and $S_{\overline{T}}$, which further corrupt the aesthetic information. Combining both factors, the randomness of fragments can help to better remove the aesthetic effects in the TQE, which serves as implicit augmentation similar to multi-scale learning on $S_{A\parallel}$ and $S_A$.

### 3.5. Fusion Strategies

After learning the disentangled representations, we further design fusion strategies for the two evaluators to assess the ability of DOVER on predicting accurate overall quality.

**Score-level Fusion.** We propose the Linear Weighted Fusion to fuse the predicted scores from both evaluators, i.e., score-level fusion. Given weights for the estimations of AQE and TQE as $W_A$ and $W_T = 1 - W_A$, respectively, we optimize $W_A$ to minimize the distance between the prediction after score-level fusion and the MOS value:

$$\min_{W_A} L_{\text{Sup}}(W_AQ_{\text{pred},A} + W_TQ_{\text{pred},T}, \text{MOS}) \quad (5)$$

**Representation-level Fusion.** To further validate the generalization ability of the representations $F_A$ and $F_T$ from AQE and TQE after fusion, we transfer them into downstream small datasets with learnable regression heads ($H_A$ and $H_T$), respectively, i.e., representation-level fusion. As the regression heads already have the ability to re-weight scores, we do not need the extra scalar weights ($W_A$ and $W_T$) and minimize the distance between the direct sum of the regressed scores from $F_A$ and $F_T$ and the MOS value:

$$\min_{\Theta_f} L_{\text{Sup}}(H_A(F_A) + H_T(F_T), \text{MOS}) \quad (6)$$

Following common practices [76, 77], we design two transfer strategies with different parameters $\Theta_f$ to optimize:

1. **head-only transfer**, i.e., $\Theta_f$ are in heads $H_A$ and $H_T$ only (Fig. 5(a)), examining critically the robustness of the DOVER representations learnt under the LVBS on different scenarios; 2. **end-to-end transfer**, i.e., $\Theta_f$ are all parameters in $M_A$ and $M_T$ (Fig. 5(b)), with the goal of optimal downstream performance and examining the ability to preserve quality-related information of two decomposed views.

### 4. Experiments

In this section, we evaluate the proposed DOVER by answering the following questions via experiments:

- Has DOVER learnt Disentangled Quality (Sec. 4.2)?
- With fusion, can DOVER predict more accurate overall quality than existing methods (Sec. 4.3&Sec. 4.4)?
- Are the frameworks for disentangling, i.e., the LVBS scheme and linear weighted fusion effective (Sec. 4.5)?
- What are the effects of the concrete designs of specific views and regularization (Sec. 4.6)?

#### 4.1. Experimental Setups

**Implementation Details.** In the AQE, we use $S_A$ with size $224 \times 224$ during inference and over-downsampled $S_{A\parallel}$ size $128 \times 128$ to better exclude technical quality issues. Temporally, we sample $N = 32$ frames sparsely from the video, which is 3 frames-per-second for a 10-second video. The backbone of the AQE is inflated-ConvNext [78] Tiny, with 27M parameters. In the TQE, we crop single patches at size $S_T = 32$ from $7 \times 7$ spatial grids and sample a clip of 32 continuous frames during training. During inference, the TQE calculates the average score from three video clips sampled at start, middle, end of the video. The backbone of the TQE is Video Swin Transformer [79] Tiny with GRPB modules [11], with 28M parameters. $\lambda_{\text{CR}} = 0.3$.

**Training and Evaluation Datasets.** In order to learn more robust representations, we train the proposed DOVER with the large-scale UGC-VQA dataset, LSVQ [5] (39,072 videos), and directly evaluate its generalization ability on three smaller UGC-VQA datasets, KoVid-1k [2] (1,200 videos), LIVE-VQC [4] (585 videos), and YouTube-UGC [34] (1,380 videos). We also evaluate on CVD2014 [18] (234 videos), which is not a UGC-VQA dataset.
4.2. Has DOVER learnt Disentangled Quality?

To evaluate whether the two evaluators can learn to predict disentangled quality, we first conduct qualitative studies (Sec 4.2.1) to prove that they can predict diverged quality evaluations reflecting different quality issues. Moreover, we conduct blind subjective studies (Sec 4.2.2) to quantitatively validate if the two evaluators can agree with human opinions on the aesthetic and technical video quality.

4.2.1 Qualitative Studies between Two Evaluators

Divergence Map. In Fig. 6, we visualize the divergence map between AQE and TQE predictions in LSVQ1080P. Considering the pairwise quality comparisons, the two evaluators only have 82% concordance though they are supervised from the same objective. Specifically, we look at edge cases (where the two evaluators have the largest divergence, noted in orange circles in Fig. 6). Among these cases, the AQE can distinguish between bad (chaotic scene, Fig. 6 downright) and good (symmetric view, Fig. 6 upleft) aesthetics, while the TQE can detect technical quality issues (blurs, over-exposure, compression errors at Fig. 6 upleft).

gMAD Examples. We conduct the group Maximum Differentiation [80] (gMAD) comparison between AQE and TQE to find video groups with similar AQE prediction but remarkably different TQE prediction (or vice versa). As shown in Fig. 7, videos with ascending TQE scores are with improving technical quality from blurs and artifacts to clear textures, and increasing AQE scores are with improving aesthetics from incomplete and occluded targets to professional composition considering rule of thirds, suggesting their sensitivity on respective aspects of quality.

4.2.2 Blind Subjective Studies on Diverged Pairs

Due to the absence of ground truth labels for disentangled video quality, we further conduct the blind subjective studies to measure whether the diverged AQE&TQE predictions match human opinions on aesthetic and technical quality.

Subjective Study Settings. We evaluate on diverged pairs \( \{V_1, V_2\} \) where AQE and TQE rank differently (e.g., AQE predicts \( V_1 \) is better yet TQE predicts \( V_2 \) is better). Specifically, video \( V_1 \) in the diverged pair should have more than \( 0.5\sigma \) higher AQE score than another video \( V_2 \) in the pair, and more than \( 0.5\sigma \) lower TQE score than \( V_2 \); or vice versa. (\( \sigma \): variance for respective scores in the whole test set). After random sampling 200 pairs, we invite 15 subjects to blindly choose which one has better aesthetic (or technical) quality in the pair without knowing AQE and TQE predictions. Their ratings are post-processed by popular votes to generate final subjective ranks on aesthetic and technical quality. Details are in Appendix (Sec. B)

Quantitative Results. The Concordance between the votes and the predictions in pairs are listed in Tab. 1. The objective AQE and TQE predictions are significantly consistent with respective human opinions on aesthetic and technical quality (even better than MOS labels), proving that the proposed DOVER achieves aesthetic-technical disentanglement. Qualitative results are in Appendix Sec. C.4.

4.3. Score-level Benchmarks

We first benchmark the DOVER with score-level fusion strategy (Eq. 5) while all methods are only trained with LSVQ and tested on different datasets to evaluate the generalization ability. The results are listed in Tab. 2 and Tab. 4. Accuracy. The proposed DOVER outperforms state-of-the-arts for intra-dataset evaluations on test subsets of...
LSVQ by improving up to 2.0% PLCC than FAST-VQA, the existing best approach. On the zero-shot generalization evaluations while the model is only trained on LSVQ but tested on diverse datasets, the DOVER has shown more competitive performance. It improves PLCC on FAST-VQA by 5.8% (for YouTube-UGC) and 3.3% (for KoNViD-1k) respectively on two UGC-VQA datasets with different types of contents generated from both professional and unprofessional users (where aesthetic difference is significant), further suggesting that the effectiveness of the AQE on modeling aesthetic-related quality perception.

**Efficiency.** Thanks to the reduced dimensions during View Decomposition (e.g., downsampling, frame sampling, patch cropping), DOVER has extraordinary efficiency that achieves real-time inference on CPU even for 1080P videos.

### 4.4. Representation-level Benchmarks

In this section, we benchmark the fused representations learnt by two evaluators by evaluating their *head-only* transfer and *end-to-end* transfer abilities (illustrated in Fig. 5). We conduct all transfer experiments in 10 random splits (random seed in \{42 \times i_{1=1}\}) with 80% of videos for training and rest 20% for testing. The results are listed in Tab. 3.

**“head-only” Transfer.** The *head-only* transfer in Tab. 3(a) directly evaluates the generalization ability of the feature representations. Compared with FAST-VQA under the same pre-training datasets and *head-only* transfer, the proposed DOVER achieves very notable improvements to FAST-VQA (with only technical-specific views) on all these datasets (up to 7.0%). The proposed DOVER with only *head-only* transfer also outperforms existing ap-

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**Table 2.** Comparison with existing methods (classical and deep) when all methods use the official training split of large-scale LSVQ [5] as training set.

| Methods | GFLOPs | CPU Time | GPU Time | LSVDQ \_\_\_ | LSVDQ | KoNiQ | LIVE-QC |
|---------|--------|----------|----------|-----------|-------|-------|--------|
| FAST-VQA (ECCV, 2022) [11] | 279.1 | 8.8s | 45ms | 0.876 | 0.877 | 0.779 | 0.814 |
| DOVER Representations (ours) | 282.3 | 9.7s | 47ms | 0.888 | 0.889 | 0.795 | 0.830 |
| – improvement to existing best | +1.5% | +1% | +2.0% | +2.5% | +2.5% | +1.6% | +1.3% |

**Table 3.** Evaluation on the fused representations in DOVER via transfer learning comparison on smaller UGC-VQA datasets and CVD2014. We note how each method obtained their representations. All methods except for the proposed DOVER and FAST-VQA are only applicable for *head-only* transfer.

**Table 4.** Extended generalization evaluations. As no current methods evaluate on these datasets, we test on released FAST-VQA (existing state-of-the-art on benchmark datasets in Tab. 2) to compare with.
proaches [5, 7, 9, 29] that pre-train on large scale IQA datasets [56, 57, 82, 83] by up to 6.7% on all UGC-VQA datasets, yet with far less computational cost. With only head-only transfer, it even out-performs FAST-VQA with end-to-end fine-tuning on some datasets. The comparisons have proved that aesthetic-related representations are important in the quality perception of UGC videos.

“end-to-end” Transfer. In end-to-end transfer shown in Tab. 3(b), the proposed DOVER also achieves notable improvements than FAST-VQA on all UGC-VQA datasets, especially the YouTube-UGC dataset where the content diversity is most significant, suggesting aesthetic-related information in videos is irreplaceable for quality evaluations on UGC videos among diverse types of contents.

4.5. Effects on Disentanglement and Fusion

Effects of the LVBS scheme. A common way [27, 29, 51] to combine two factors in quality assessment is Feature Aggregation (regressing concatenated features of two backbones to overall scores). However, as evaluated in Tab. 6, the proposed LVBS scheme is notably better than Feature Aggregation, suggesting that the two factors are more likely to affect human perception in an independent way.

Effects of Both Evaluators. In Tab. 7, we separately evaluate the SRCC and PLCC for predictions of two individual evaluators to the overall MOS. Thanks to the LVBS, both two evaluators have achieved competitive performance independently. On the other hand, the full DOVER is also notably better than any single evaluator, demonstrating the two evaluators are practically focusing on different quality-related issues in the UGC-VQA problem.

Effects of Linear Weighted Fusion. We discuss the effects of weighted fusion as proposed in Sec. 3.5. As shown Tab. 7, if we directly obtain the fused quality as \( Q_{\text{pred},A} + Q_{\text{pred},T} \) without weights, the overall predictions will be less accurate than with fusion weighting, proving that two quality issues have different effects on final quality.

4.6. Effects on Concrete Designs

In the next part, we discuss the effects of different concrete designs. As the technical-specific views in the TQE are following designs validated in FAST-VQA [11], we only evaluate effects of designs on aesthetic-specific views, pre-training and regularization strategies (Eq. 4) in the AQE.

Effects on Aesthetic-specific Views. We discuss the design of aesthetic-specific views in Group 1 of Tab. 5. Specifically, we prove that the spatial downsampling is far better than cropping: the cropping does not only have worse performance for the AQE itself but also brings almost no contributions to the overall accuracy. Keeping spatial aspect ratio also leads to a bit worse overall performance. Similarly, the temporal sparse sampling is also far better than continuous frames. The spatial and temporal comparisons demonstrate that retaining all objects and their organizations is important in preserving the aesthetics of videos.

Effects on Regularization Strategies. The effects of the multi-scale learning for the AQE (as in Eq. 4) are shown in Tab. 5 Group 2. On the one hand, it does not improve the independent accuracy of the AQE. Nevertheless, it proves better overall accuracy on all evaluation sets. The results have suggested the multi-scale learning further avoids the technical effects for the AQE and effectively diversifies the two evaluators, contributing to the final disentanglement.

5. Conclusion and Outlook

In this paper, we make the first attempt to disentangle aesthetic and technical effects in the UGC-VQA problem, the DOVER, that effectively separates aesthetic and technical quality of videos without respective supervisions, and also reaches state-of-the-arts for overall quality evaluation on all UGC-VQA datasets. We look forward to future works to further improve decoupled video quality evaluators under the proposed LVBS scheme which proves to be effective.
A. Acknowledgement

This study (including the proposed DOVER and the blind subjective studies) is supported under the RIE2020 Industry Alignment Fund – Industry Collaboration Projects (IAF-ICP) Funding Initiative, as well as cash and in-kind contribution from the industry partner(s). The published codes are licensed under the MIT License and NTU S-Lab License that allows redistribution and use for non-commercial purpose in source and binary forms.

Special thanks to Annan Wang, designer of the interfaces for blind subjective studies, and all participants for studies, whose efforts are moving the field of VQA forward.

B. The Process of Blind Subjective Studies

B.1. Before Experiments: Data Preparation

Data Source. The videos used for the Blind Subjective Studies are from the two test sets of LSVQ [5] dataset: LSVQ_{test} and LSVQ_{1080p} (the largest test sets), and the proposed DOVER is trained on the corresponding training set of LSVQ. To make sure that the resolution of videos does not affect subjective ratings, we only select pairs where both videos are in LSVQ_{test} or LSVQ_{1080p} (100 pairs each). We also remove the ia_batch1 subsets in LSVQ as these subsets contain several videos composed of still images.

Why Evaluate on Diverged Pairs? In a proportion of videos, the professionalism of photographers is associated with what technical equipment they would use to record or generate a video. The existence of these videos could lead to the relatively good overall performance on the biased evaluators (AQE and TQE): they are focusing on different aspects of the video quality but they happen to be similar. These videos cannot reflect the ability of the AQE and the TQE on separation the perceptions between the two issues. The videos with diverged AQE and TQE predictions, though, could be potentially the other proportion of videos with different aesthetic and technical quality, and henceforth selected for subjective studies to evaluate the disentanglement ability of DOVER. Following conclusions of several recent studies [84–86], we evaluate on the results of pairwise rank comparisons instead of direct quality score. The selection process for pairs is discussed as follows.

Selection for Diverged Pairs. To select the pairs where the two evaluators (the AQE and the TQE) predict differently with high confidences, we first normalize the predictions of each evaluator, so that the scores of both evaluators follow the Gaussian distribution $N(0, 1)$ as follows:

$$\hat{E}(Q_{V,A}) = \frac{E(Q_{V,A}) - E(Q_{V,A})}{\sigma(E(Q_{V,A}))}$$

$$\hat{E}(Q_{V,T}) = \frac{E(Q_{V,T}) - E(Q_{V,T})}{\sigma(E(Q_{V,T}))}$$

Then, to select the diverged video pair $(V_1, V_2)$, we constrain that $\hat{E}(Q_{V_1,T}) - \hat{E}(Q_{V_1,T}) > 0.5$ and $\hat{E}(Q_{V_2,A}) - \hat{E}(Q_{V_2,A}) < -0.5$, or vice versa. These diverged pairs are the video pairs where the proposed DOVER recognizes that one video has notably better aesthetic quality, but another has notably better technical quality.

After pair selection, 200 random pairs (with seed 42) are sampled from all feasible pairs for subjective studies.

Information on Subjects. We invite 15 subjects with age 19 to 25 and residing in two different countries, where each subject is instructed to provide 400 binary opinions (200 pairs of both aesthetic and technical quality). Prior to our study, the subjects do not know each other; during annotation, each subject is unable to view annotations from other subjects to avoid influences from one another.
B.2. During Subjective Studies

Annotation Interface. The annotation interfaces for aesthetic and technical quality comparisons are illustrated in Fig. 8 and Fig. 9 respectively. In addition, to avoid Internet-transmission-based stalling that may degrade the quality of original videos [18, 24] and distract the comparison, we require the annotators to download all videos into local directories first and annotate through a local browser.

Instructions for aesthetic comparison.
In this task, you are instructed to assess which one has better aesthetic quality between two videos, specifically based on the following aspects:
1. Do the video contents have clear, appealing or meaningful semantics?
2. Do the video has good composition, i.e. do the target objects occur in good positions of the video?
3. Can you understand what the video is about?
   Please be at most subjective on judging which video has overall better aesthetics by your preference, **WITHOUT** considering the following aspects:
1. The textures
2. The artifacts, and noises
3. The picture clearness (whether it is blurry or not)
4. Other technical-related issues
   We advise you to view the videos without zooming and view only once to have a overall subjective judgement on the aesthetics of this video.

Instructions for technical comparison.
In this task, you are instructed to assess which one has better technical quality between two videos, only based on the following aspects:
1. The artifacts, and noises (stronger is worse)
2. The temporal quality: does the video have very strong flicker? (stronger is worse)
3. The picture clearness (whether it is blurry or not)
4. Other technical-related issues
   In this part, we advise you to zoom each video into full screen; for better judgement, you may stop at middle of the video to see more clearly.
   Be sure **not to consider** the contents / composition in the videos during the stage of technical evaluation.

Training videos. Besides randomly selecting 200 pairs of videos from all video pairs that follow our data preparation requirements for the blind annotations, we also select 10 pairs as training videos with gold subjective labels (i.e. certificated ground truth binary opinions on both aesthetic and technical quality comparison between the videos the pairs) from the research team to train the subjective evaluators prior to their subjective studies. The training video pairs are also randomly mixed in the video pairs that are needed to be annotated and the opinions of the annotator is valid only when he/she correctly labels more than 70% (7/10 for both comparisons) training video pairs.

C. Extended Qualitative Results
C.1. Feature Dissimilarity Curves
As discussed in Sec. 3.3, features for different scales of aesthetic-specific views are dissimilar. In Fig. 12, we further illustrate that the dissimilarity practically exists in the multi-scale learning process of the AQE even when different scales of aesthetic-specific views are both supervised from the same ground truth MOS. The dissimilarity could be removed by the proposed Cross-Scale Restraint.

C.2. More Divergence Maps
Fig. 10 and Fig. 11 show the divergence maps on LSVQtest, LIVE-VQC, KoNVid-1k and YouTube-UGC respectively. The DOVER on all these datasets show divergent predictions on the two evaluators, especially the YouTube-UGC where the two evaluators only have 0.793 SRCC, 0.810 PLCC, 0.603 KRCC and 80.1% concordance.
Figure 10. The divergence between aesthetic and technical evaluation by the proposed DOVER model in LIVE-VQC [4] and LSVQ-test [5].

Figure 11. The divergence between aesthetic and technical evaluation by the proposed DOVER model in KoNViD-1k [2] and YouTube-UGC [34].

Figure 12. Dissimilarities between different S_A downsampled to 128 × 128 (denoted as S_A↓) and 224 × 224. With the Cross-scale Restraint, the AQE can extract consistent aesthetic-related representations across scales.

In LIVE-VQC, two evaluators are relatively similar (0.906 SRCC, 86.7% concordance), which might be due to the limited diversity of input contents (all videos are shot by smartphones on common events or objects, without post-production). We also notice that though in general the TQE predictions have better correlation with MOS labels, in the edge cases the AQE is usually more accurate, which might be suggesting that aesthetic quality is usually not so much deviated in UGC videos but with bad aesthetics can significantly degrade the overall quality of videos.

C.3. Statistics on Different Datasets

To compare the overall quality between different VQA datasets, we visualize the distributions of predicted aesthetic and technical quality of videos in different datasets under the same model of DOVER. As all the scores are predicted via the same model (and weights) and reach very good relative correlation with every single dataset, we can utilize the statistical information about the predicted scores as a reference for the quality distributions of different datasets. As illustrated in Fig. 13, LIVE-VQC has the
Figure 13. Distributions of aesthetic quality evaluation (AQE score) and technical quality evaluation (TQE score) for different datasets.

Figure 14. Success case (I) when the proposed DOVER can disentangle the aesthetic and technical quality of videos. The video in the left has apparently better aesthetics (good composition) but worse technical quality due to the distortions (blurs, noises, color errors, under-exposures).

The best technical quality (while compression processes are excluded in this dataset) among all sets, yet LSVQ_{1080P} has better overall aesthetic quality (while a proportion of videos are shot by professional users). LSVQ_{test} contains more old videos (which were created decades ago) from the Internet Archive (IA) [87] (48%) than LSVQ_{1080P} (23%), causing the difference between their aesthetic quality distributions (LSVQ_{1080P} has sharper distributions). The KoNViD-1k is the worst for both quality evaluation among all datasets and is also the earliest one among them, suggesting the overall quality of UGC videos are improving during recent years.
Figure 15. Success case (II) when the proposed DOVER can disentangle the aesthetic and technical quality of videos. The video in the left has apparently better aesthetics (symmetry composition, clear semantics) but relative worse technical quality due to the distortions (blurs).

Figure 16. Success case (III) when the proposed DOVER can disentangle the aesthetic and technical quality of videos. The video in the left has apparently better aesthetics with almost every subjects agreed (with very good content for photography: sunset) but worse technical quality due to the distortions from the perspective of technical evaluation (over-exposure, blurs).
Figure 17. A typical failure case of DOVER on disentangling aesthetic and technical quality. The video in the right has very strong compression artifacts where the one in the left is very blurry: the TQE prefers the right while subjective opinions slightly prefer the left. The difference is similar between aesthetic predictions and subjective opinions. These failure cases suggest that the DOVER can still be improved on finer-grained cases.

C.4. Qualitative Analysis on Blind Subjective Studies

C.4.1 Success Cases
We visualized several successful cases (i.e. when the subjective annotators agree with both aesthetic and technical comparison of DOVER between videos in the diverged pair) for the aesthetic-technical disentanglement via the proposed DOVER in Fig. 14, Fig. 15 and Fig. 16. Specifically, we can notice that the TQE is very sensitive to textures especially clearness of videos, and is also sensitive to global technical quality factors such as under-exposure (Fig. 14, left) and over-exposure (Fig. 16, left). On the contrary, the AQE not only very sensitive on the chaotic compositions and distinguish them as bad aesthetics, but also able to recognize commonly-agreed good aesthetics as in (Fig. 16, left). These cases further demonstrates the effectiveness of the DOVER on disentangling both effects in UGC-VQA.

C.4.2 Failure Cases: the “finer-grained” Quality
Without respective supervision, the proposed DOVER is not perfect on decoupling aesthetic and technical effects with still around 30% error predictions (26% for technical, 31% for aesthetics). When we look at the failure cases, we notice that most of them are pretty “finer-grained” cases where there are different aesthetic and technical concerns in the two videos of the pair, as illustrated in Fig. 17. For the video in the left, there are some typical light spots which are usually preferred in photography, yet the content is relatively meaningless compared with the right one. For technical considerations, the left one is much more blurry but the other is with unacceptable artifacts from compression. This cases suggest that though DOVER could be able to consider different issues for TQE and AQE, it is still not so well in better reasoning their effects in aesthetic and technical perception of video quality, especially in the finer-grained cases. To achieve finer-grained predictions, the optimal way would be introducing separate supervisions, yet this is currently unavailable in existing UGC-VQA datasets.

C.5. Evaluation Results on In-the-Wild Videos
Quality assessment datasets might have different quality distribution from in-the-wild videos due to data pre-filtering processes [2,4]. Thus, to examine the generalization ability of the proposed DOVER on its both aesthetic and technical evaluators, we direct test it on a randomly sampled 3000-video subset of Kinetics-400 [88], an action recognition dataset directly collected from UGC videos on YouTube platform. As illustrated in Fig. 18, the AQE and TQE in the proposed DOVER can effectively identify aesthetic or tech-
Worst Technical on in-the-wild Test Set (Unacceptable Compression Artifacts)

Best Technical on in-the-wild Test Set (Sharp, Stable, no Artifacts, no Motion Blur or Noises)

Worst Aesthetic on in-the-wild Test Set (Upside Down, Chaotic, Unappealing Content)

Best Aesthetic on in-the-wild Test Set (Meaningful, Good Composition: rule-of-thirds, Shallow Depth-of-Field)

Figure 18. Videos with worst and best aesthetic and technical quality on the in-the-wild test set sub-sampled from Kinetics-400 [88], effectively reflecting human perception on aesthetic and technical quality of videos.

D. Detailed Structures of Evaluators

D.1. the Aesthetic Quality Evaluator

Equation for the Aesthetic-specific Views. Given a video \( V = \{ V_i | i = 0, 1, \ldots, T - 1 \} \) with \( T \) total frames, the aesthetic-specific views \( S_A \) with \( N \) sparse frames and spatial size \( s \) are formulated as:

\[
\mathcal{F} = \{ V_{i(\frac{j}{N_s}, \frac{(j+1)}{N_s})} | j = 0 \}^{T-1} = \{ F_i | i = 0 \}^{N-1}
\]

\[
S_{A,i} = \text{downsample}(b \otimes F_i, s)
\]

where \( \mathcal{F} \) is the remained frames after sparse sampling (\( F_i \) is the \( i \)-th frame in it), \( b(a, b) \) denotes uniform index sampling between \( (a, b) \), \( b \) is the blur kernel, \( \otimes \) denotes element-wise multiplication, and \( \text{downsample}(\cdot, s) \) denotes downsampling a frame into size \( s \times s \). Moreover, the over-downsampled views \( (S_{A,\downarrow}) \) is defined as follows:

\[
S_{A,i,\downarrow} = \text{downsample}(\text{downsample}(b \otimes F_i, s), s^{-})
\]

where \( s^{-} \) is the size for the over-downsampled views.

Cross-scale Friendly Feature Extractor. Following existing practices [7], we include the ImageNet-1k [54] pre-trained backbone as the content extractor for the AQE. We also choose a traditional convolution-based backbone ConvNeXt [78] to be friendly to multi-scale learning. As the temporal content relations are also noticed to be influential in the UGC-VQA problem [31, 70], we inflate the 2D ConvNeXt backbone with strategies as in [89] with the “1, 1, 3” inflation strategy to better consider both spatial and temporal aesthetic information in UGC videos.

D.2. the Technical Quality Evaluator

Equation for Technical-specific Views. The Technical-specific Views \( (S_T) \) [11] are formulated as:

\[
S_{T,i,u,v} = R_{\text{crop}}(V_{i}, u \times S_{f}, v \times S_{f})
\]

where \( P_{i,u,v} \) is the patch at the \( i \)-th frame, \( u \)-th horizontal grid, \( v \)-th vertical grid. \( G_f \times G_f \) is the number of grids
where patches are cropped, and \( \text{RCrop}(\cdot, s_f) \) denotes randomly cropping a patch sized \( s_f \times s_f \).

**Patch-based Feature Extractor.** To adapt to the characteristics of \( S_T \), we choose the patch-based Swin-GRPB backbone as proposed in [11]. The feature extractor is pre-trained with Kinetics-400 [89], which is collected on YouTube and contains lots of technical quality distortions.

### E. More Implementation Details

#### E.1. Training Objective \( \mathcal{L}_{\text{Sup}} \)

In this section, we discuss the concrete design of the training loss function \( \mathcal{L}_{\text{Sup}}(\cdot, \text{MOS}) \) (the supervised loss). Inspired by several studies [52, 90, 91], we restrain the monotonicity between predicted scores and MOS (\( \mathcal{L}_{\text{mono}} \)) and the linearity between them (\( \mathcal{L}_{\text{lin}} \)). The fusion linearity-monotonicity loss is defined as follows, which is the same as existing state-of-the-arts [11, 29]:

\[
\mathcal{L}_{\text{mono}} = \sum_{i,j} \max((Q_{\text{pred}}^i - Q_{\text{pred}}^j) \text{sgn}((\text{MOS}^j - \text{MOS}^i), 0) \tag{15}
\]

\[
\mathcal{L}_{\text{lin}} = (1 - \frac{(Q_{\text{pred}} - Q_{\text{pred}}) \cdot (\text{MOS} - \text{MOS})}{\|Q_{\text{pred}} - Q_{\text{pred}}\|_2\|\text{MOS} - \text{MOS}\|_2})/2 \tag{16}
\]

\[
\mathcal{L}_{\text{sup}} = \mathcal{L}_{\text{lin}} + 0.1 \mathcal{L}_{\text{mono}} \tag{17}
\]

where \( \text{sgn}(\cdot) \) denotes the sign function, \( a \cdot b \) denotes the inner product of \( a \) and \( b \), and \( Q_{\text{pred}} \) and MOS are vectors that refer to predictions and ground truth labels in a batch.

#### E.2. Evaluation Metrics

We introduce the Pearson linear correlation coefficient (PLCC) and the Spearman’s rank-order correlation coefficient (SRCC) as evaluation metrics. PLCC computes the linear correlation between a series of predicted scores \( Q_{\text{pred}} \) and ground truth scores MOS, while SRCC assesses the rank correlation. They are formulated as below:

\[
\text{PLCC} = \frac{(Q_{\text{pred}} - Q_{\text{pred}}) \cdot (\text{MOS} - \text{MOS})}{\|Q_{\text{pred}} - Q_{\text{pred}}\|_2\|\text{MOS} - \text{MOS}\|_2} \tag{18}
\]

\[
\text{SRCC} = 1 - \frac{6 \sum_{i=1}^{N} d_i^2}{N(N^2 - 1)} \tag{19}
\]

where \( \mu(\cdot) \) is the mean value, \( d_i \) is the distance of rank orders between predictions and ground truth of video \( i \).

We also include the concordance \( C \) (a metric for agreement between two binary rank evaluators, higher is better) as the evaluation metric for the results of blind subjective studies, which is calculated as follows:

\[
C = \frac{\text{concordant pairs}}{\text{concordant pairs} + \text{discordant pairs}} \tag{20}
\]

Specifically, for our subjective studies, a concordance pair means that at least 8 (among 15) subjective annotators agree with the corresponding objective prediction by DOVER, which others are considered as discordant pairs.

### F. Limitations

As the first work to explore disentangled video quality assessment (VQA) without corresponding labels, we do our best to overcome the difficulties that exist practically. We propose the Limited View Biased Supervision (LVBS) scheme for training, and subjective studies on 200 pairs of videos for evaluation. The results are relatively good considering the lack of labels, yet the disentanglement effect under weakly-supervised LVBS schemes is still difficult to match with ideal (but currently unavailable) fully-supervised schemes, as analyzed in our failure cases (Sec. C.4.2) section. Furthermore, the scale of current subjective studies in our paper is still not large enough to serve for training and may also contain biases to serve for evaluation. We sincerely hope that the disentanglement of aesthetic and technical effects in VQA will receive more attention from researchers, and we look forward to joint efforts for larger-scale subjective studies on this problem.

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