DEEP VQA BASED ON A NOVEL HYBRID TRAINING METHODOLOGY

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ABSTRACT

In recent years, deep learning techniques have been widely applied to video quality assessment (VQA), showing significant potential to achieve higher correlation performance with subjective opinions compared to conventional approaches. However, these methods are often developed based on limited training materials and evaluated through cross validation, due to the lack of large scale subjective databases. In this context, this paper proposes a new hybrid training methodology, which generates large volumes of training data by using quality indices from an existing perceptual quality metric, VMAF, as training targets, instead of actual subjective opinion scores. An additional shallow CNN is also employed for temporal pooling, which was trained based on a small subjective video database. The resulting Deep Video Quality Metric (based on Hybrid Training), DVQM-HT, has been fully tested on eight HD subjective video databases, and consistently exhibits higher correlation with perceptual quality compared to other deep quality assessment methods, with an average SROCC value of 0.8263.

Index Terms— Video quality assessment, deep learning, hybrid training, perceptual quality.

1. INTRODUCTION

Objective video quality assessment (VQA) metrics provide an essential tool for efficiently predicting video quality and benchmarking video processing algorithms [1]. More recently, perceptual quality metrics have also been employed as loss functions for training deep learning based approaches, playing a critical role in model optimisation and stabilisation [2].

Dependent on the availability of reference content, objective VQA methods can be classified into three sub-groups: full reference (FR), reduced reference (RR) and blind reference (BR). RR and BR models require either partial or no information about the reference video, while FR approaches use both the reference and the distorted video content as inputs. The focus of this paper is solely on FR quality metrics.

Among existing FR VQA methods, PSNR and SSIM [3] are the most widely used approaches due to their low computational complexity. To achieve better correlation performance with visual quality, many perceptually optimised quality metrics have been proposed including a series of SSIM variants [4–6], MAD [7], STMAD [8], MOVIE [9] and PVM [10]. More recently, Netflix has developed a machine learning based quality metric, Video Multimethod Assessment Fusion (VMAF) [11], combining six different video features using a support vector regressor (SVR). Although some of these methods have provided consistent correlation performance with subjective opinions, over a wide range of content and distortion types they tend to have relatively high computational complexity and/or are not differentiable (and hence are unsuitable for use as perceptual loss functions in CNN training).

In recent years, deep neural networks have been increasingly applied to image [12–14] and video [15–18] quality assessment. These methods have demonstrated the potential to compete with conventional quality metrics, while also being differentiable. In addition, due to the limited cardinality of available subjective databases, most deep VQA methods [15–18] have been trained and evaluated on small databases through cross validation. This can result in overfitting problems and inconsistent performance across different content types.

Inspired by previous works in [18–20], we propose a new hybrid training methodology for deep video quality assessment. In this work, a 3D convolutional neural network (CNN) was trained on a large database, which contains diverse source content from BVI-DVC [21] and distorted videos generated by three modern video codecs alongside resolution adaptation [22]. Instead of using ground-truth subjective data as the training target, VMAF quality indices were calculated for all the input sequences. This facilitates a much larger training dataset, which helps to achieve model generalisation and alleviate overfitting issues. To further improve the overall quality prediction performance, we have also employed an additional CNN for temporal pooling, which was trained separately based on a smaller database with subjective data. The proposed method, DVQM-HT, has been comprehensively tested on eight subjective video databases, outperforming all the benchmark deep quality metrics.
The rest of the paper is organised as follows. Section 2 describes the employed network architecture and the proposed hybrid training method in detail. Section 3 presents the experimental configuration and the evaluation databases. The experimental results are shown in Section 4 with analysis. Finally, Section 5 concludes the paper and outlines future work.

2. PROPOSED ALGORITHM

In this section, we present the employed CNN architectures and the proposed training methodology.

2.1. The Employed Network Architecture

The proposed Deep Video Quality Metric (based on the Hybrid Training method), DVQM-HT, first employs a 3D-CNN to predict a quality index for two image patches (256×256×3 in this case). The architecture of the network is similar to that used in [16], but with the following modifications: (i) we used 3D convolutions rather than 2D in the first two convolutional layers, which are used to process the error map and the distorted patch, in order to better extract spatiotemporal information; (ii) the original activation functions in [16] are replaced by Leaky ReLU (LReLU). An illustration of the 3D-CNN network is shown in Fig. 1, where the network implementation details including channel number, kernel sizes, stride and padding are labelled in detail.

When the quality indices of all the patches for the current frame are obtained, their arithmetic mean is calculated as the quality index for this frame. In order to improve temporal pooling, a temporal aggregation network is used to obtain the final sequence level quality score. The network structure is based on the STAN architecture developed in [17], as shown in Fig. 2.

2.2. Training Database and Methodology

As mentioned in Section 1, subjective video databases with a small number of test sequences are not suitable for training relatively deep CNN-based VQA models. To solve this problem, a hybrid training methodology was employed in this work. First, based on previous works in [18–20], we have used a perceptual quality metric instead of the limited subjective ground truth to generate a large amount of training material for optimising the 3D-CNN network. The quality indices produced by this network are then fed into the second shallow CNN for temporal aggregation, which was trained based on a small video database with subjective ground truth information. It should be noted that our hybrid solution cannot be an optimal solution, because the correlation between VMAF and perceptual quality is not perfect. However, due to the lack of large scale subjective video quality databases, this training methodology offers a trade-off between good model generalisation and superior correlation with subjective opinions.

To generate the training content, we used the 200 HD source sequences from the BVI-DVC database [21], which

Table 1: The employed video codecs and configurations.

| Codec  | Version | Configuration parameters                  |
|--------|---------|------------------------------------------|
| HEVC HM| 16.20   | Random access configuration [23]. QP=[32,37,42,47] |
| AOM AV1| 1.0-0.5ec3e8c| The same configuration as in [24]. QP=[32,43,55,63] |
| VVC VTM| 7.0     | Random access configuration [25]. QP=[32,37,42,47] |

1In this paper, we solely focus on HD resolution sequences.
contains diverse and representative natural content and covers different scenes and objects. Each source video has 64 frames in 10 bit YCbCr 4:2:0 format. These sequences were compressed using three different video codecs: the High Efficiency Video Coding Test Model (HM) [26], AOMedia Video 1 (AV1) [27] and the Versatile Video Coding Test Model (VTM) [28], at four quantization levels to create diverse distortion types. The codec versions and configurations are summarised in Table 1.

In addition to compression-distorted sequences, we have also generated training content with resolution adaptation artifacts, as these are also common in video streaming scenarios [22]. Specifically, all the 200 source sequences were first down-sampled to three lower spatial resolutions, 720p, 540p, and 360p using the Lanczos3 [29] filter. These low resolution sequences were then compressed by the three codecs described above with the same coding configurations. The compressed content was then decoded and up-sampled to their original resolution using a nearest neighbour filter. This increases the distortion diversity and quality range of the training data, and results in a total number of 9600 (200 sources × 4 resolutions × 3 codecs × 4 quantization levels) distorted sequences.

Each distorted sequence and its original counterpart were then randomly cropped by a non-overlapping spatiotemporal sliding window of size of 256 × 256 × 3, which generates reference and distorted patch pairs (Y channel only) as shown in Fig. 1. A VMAF quality index was then calculated for each patch pair. VMAF was selected due to its consistent performance across different test databases [30] and its relatively low complexity. This generated approximately 614,400 pairs of patches associated with the same number of VMAF values, which were used to train the employed 3D-CNN model.

For training the temporal aggregation network, we used all the sequences and their subjective scores from the VMAF-plus [11] database (used for training the original VMAF metric). The frame level quality indices were first calculated using the trained 3D-CNN model, and these indices (inputs), together with their corresponding sequence level subjective scores (targets) were used to train the temporal aggregation network.

3. EXPERIMENT CONFIGURATION

3.1. Training Configuration

We used Pytorch 1.7 to implement both networks, with the following training parameters: \( L_2 \) as the loss function; Adam optimisation [31] with hyper-parameters of \( \beta_1=0.9 \) and \( \beta_2=0.999 \); 50 training epochs; batch size of 32; the initial learning rate is 3e-4 with a weight decay of 1e-2 for 10 epochs. Both training and evaluation were executed on the BlueCrystal [32] cluster computer at the University of Bristol, which have GPU nodes with 2.4GHz Intel CPUs and NVIDIA P100 graphic cards.

3.2. Evaluation Dataset and Configuration

To comprehensively evaluate the generalisation performance of the proposed algorithm, eight different HD\(^1\) VQA datasets were carefully selected, including NFLX [11], NFLX-P [11], BVI-HD [33], CC-HD [24], CC-HDDO [34], MCL-V [35], SHVC [36], VQEGHD3 [37]. These databases contain various distortion types produced by spatial resolution adaptation and compression.

In the evaluation stage, given a distorted sequence and the corresponding reference, each frame (except the first and the last ones) and its two neighbouring frame are firstly segmented into non-overlapping 256×256×3 spatiotemporal blocks (luma component only) as the 3D-CNN input. The output quality indices for all these patches are then averaged to obtain the quality index for this frame. All the frame level quality indices are then fed into the temporal aggregation network (shown in Fig. 2) to calculate the final sequence level quality score.

4. RESULTS AND DISCUSSION

To benchmark the performance of the proposed deep VQA method, DVQM-HT, we have compared its correlation performance with eight full reference quality assessment methods, including three conventional quality metrics, PSNR, SSIM [3], MS-SSIM [4], four deep quality assessment methods\(^2\), WaDIQA [12], DeepQA [13], DeepVQA [15], C3DVQA [16], and one SVM regression based VQA approach, VMAF [11]. For all the deep learning-based metrics, i.e. WaDIQA, DeepQA, DeepVQA and C3DVQA, we used their publicly available pre-trained models for benchmarking.

To assess the performance of each quality metric, the Spearman Rank Order Correlation Coefficient (SROCC) was calculated for each database between predicted quality indices and ground truth subjective scores. Additionally, a significance test was performed between the proposed method, DVQM-HT, and other tested metrics on all test datasets. Here the F-test based approach [10, 38] was conducted on the residual between the predicted quality indices (based on a non-linear regression) and the subjective ground truth.

To further evaluate the contributions of the 3D-CNN and the temporal aggregation network, two additional DVQA-HT variants were implemented: (i) DVQM-HT (2D) replaced all the 3D convolutional layers with 2D versions (other parameters remain the same) and (ii) DVQM-HT (w/o TA) replaced the temporal aggregation network with simple arithmetic mean for temporal pooling. The same training databases and methodologies were employed for optimising both variants.

\(^2\)The selection of benchmark deep VQA methods are based on the reported performance in the original literature and the availability of their pre-trained models.
Table 2: Performance of the proposed method and other benchmark approaches on eight test databases. The values in each cell x(y) correspond to the SROCC value (x) and F-test result (y) at 95% confidence interval. y=1 suggests that the metric is superior to DVQM-HT (y=-1 if the opposite is true), while y=0 indicates that there is no significant difference between them. The figures in color red and blue indicate the highest and second highest SROCC values respectively in each column.

| SROCC/F-test | NFLX | NFLX-P | BVI-HD | CC-HD | CC-HDDO | MCL-V | SHVC | VQEGHD3 | Overall | Complexity |
|--------------|------|--------|--------|-------|---------|-------|------|---------|---------|-----------|
| PSNR         | 0.6218 (-1) | 0.6595 (-1) | 0.6145 (-1) | 0.6166 (-1) | 0.7497 (-1) | 0.4640 (-1) | 0.7380 (-1) | 0.7518 (-1) | 0.6520 | 0.35 x |
| SSIM         | 0.5603 (-1) | 0.6054 (-1) | 0.5992 (-1) | 0.7194 (0) | 0.8026 (-1) | 0.4018 (-1) | 0.5446 (-1) | 0.7361 (-1) | 0.6216 | 0.38 x |
| MS-SSIM      | 0.7136 (-1) | 0.7394 (-1) | 0.7652 (0) | 0.7535 (0) | 0.8321 (0) | 0.6306 (-1) | 0.8007 (0) | 0.8457 (-1) | 0.7601 | 0.47 x |
| WaDiQA       | 0.5713 (-1) | 0.6593 (-1) | 0.6645 (-1) | 0.6518 (-1) | 0.7041 (-1) | 0.6072 (-1) | 0.6707 (-1) | 0.6731 (-1) | 0.6910 | 0.12 x |
| DeepQA       | 0.7298 (-1) | 0.6995 (-1) | 0.7106 (-1) | 0.6202 (-1) | 0.6705 (-1) | 0.6705 (-1) | 0.7176 (-1) | 0.7881 (-1) | 0.7024 | 1.76 x |
| DeepVQA      | 0.7352 (-1) | 0.7609 (-1) | 0.7330 (0) | 0.6924 (-1) | 0.8120 (0) | 0.6142 (-1) | 0.9041 (0) | 0.7805 (-1) | 0.7540 | 4.05 x |
| C3DVQA       | 0.7730 (-1) | 0.7714 (-1) | 0.7393 (0) | 0.7203 (0) | 0.8137 (0) | 0.7126 (0) | 0.8494 (0) | 0.7329 (-1) | 0.7641 | 3.37 x |
| VMAF 0.6.1   | 0.9254 (0) | 0.9104 (0) | 0.7962 (0) | 0.8723 (1) | 0.8783 (0) | 0.7766 (0) | 0.9114 (0) | 0.8442 (0) | 0.8644 | 1 x |
| DVQM-HT (2D) | 0.8675 (0) | 0.8824 (0) | 0.7396 (0) | 0.7681 (0) | 0.8486 (0) | 0.7429 (0) | 0.8109 (0) | 0.8398 (0) | 0.8125 | 1.33 x |
| DVQM-HT (w/o TA) | 0.8793 (0) | 0.8816 (0) | 0.7583 (0) | 0.7792 (0) | 0.8523 (0) | 0.7678 (0) | 0.8238 (0) | 0.8501 (0) | 0.8190 | 3.24 x |
| DVQM-HT      | 0.8812 | 0.8883 | 0.7612 | 0.7794 | 0.8568 | 0.7796 | 0.8234 | 0.8507 | 0.8263 | 3.68 x |

Table 2 summarises the performance results on all eight test databases. It can be observed that the proposed method outperforms other deep learning based quality metrics, WaDiQA, DeepQA, DeepVQA and C3DVQA on all test datasets. The improvement here is statistically significant on at least three database (for C3DVQA) based on the F-test results. Compared to the conventional quality assessment methods and VMAF, DVQM-HT offers higher average SROCC values than PSNR, SSIM, and MS-SSIM, but is second to VMAF. However the difference between DVQA-HT and VMAF is only significant (according to the F-test) on the CC-HD database. We also observe that both DVQM-HT variants perform slightly worse than its full version on all test databases, which verifies the effectiveness of the 3D-CNN and temporal aggregation network.

Complexity wise, the proposed method is 3.68 times slower compared to VMAF, while the complexity of its 2D version, DVQM-HT (2D), is close to that of VMAF (1.33×).

5. CONCLUSION

In this paper, we proposed a new deep VQA method based on a hybrid training methodology, which supports the use of a large scale training database to optimise deep CNNs for quality assessment. The proposed method, DVQM-HT, was fully tested on eight subjective databases, and is demonstrated to consistently offer higher correlation performance compared to other deep learning based and conventional VQA methods. More importantly, this metric (and its variants) can also be used as perceptual loss functions for optimising various CNN-based video processing applications due to its relatively low complexity and differentiability property. Future work should focus on more sophisticated temporal pooling algorithms and further complexity reduction. The source code of the proposed VQA method, DVQA-HT, and its two variants will be published at https://chenfeng-bristol.github.io/DVQM-HT

References

[1] D. R. Bull and F. Zhang, *Intelligent image and video compression: communicating pictures*. Academic Press, 2021.

[2] J. Johnson, A. Alahi, and L. Fei-Fei, “Perceptual losses for real-time style transfer and super-resolution,” in *European conference on computer vision*. Springer, 2016, pp. 694–711.

[3] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.

[4] Z. Wang, E. P. Simoncelli, and A. C. Bovik, “Multi-scale structural similarity for image quality assessment,” in *Proc. Asilomar Conference on Signals, Systems and Computers*, vol. 2. IEEE, 2003, p. 1398.

[5] A. Rehman, K. Zeng, and Z. Wang, “Display device-adapted video quality-of-experience assessment,” in *Human Vision and Electronic Imaging XX*, vol. 9394. International Society for Optics and Photonics, 2015, p. 939406.

[6] Z. Wang, L. Lu, and A. C. Bovik, “Video quality assessment based on structural distortion measurement,” *Signal processing: Image communication*, vol. 19, no. 2, pp. 121–132, 2004.

[7] P. V. Vu, C. T. Vu, and D. M. Chandler, “A spatiotemporal most-apparent-distortion model for video quality assessment,” in *2011 18th IEEE International Conference on Image Processing*, 2011, pp. 2505–2508.

[8] ——, “A spatiotemporal most-apparent-distortion model for video quality assessment,” in *2011 18th IEEE International Conference on Image Processing*, 2011, pp. 2505–2508.

[9] K. Seshadrinathan and A. C. Bovik, “Motion tuned spatio-
temporal quality assessment of natural videos," *IEEE Transactions on Image Processing*, vol. 19, no. 2, pp. 335–350, 2010.

[10] F. Zhang and D. R. Bull, “A perception-based hybrid model for video quality assessment,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 26, no. 6, pp. 1017–1028, 2016.

[11] Z. Li, A. Aaron, I. Katsevounidis, A. Moorthy, and M. Manohara, “Toward a practical perceptual video quality metric,” *The Netflix Tech Blog*, 2016.

[12] S. Bosse, D. Maniry, K.-R. Müller, T. Wiegand, and W. Samek, “Deep neural networks for no-reference and full-reference image quality assessment,” *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 206–219, 2018.

[13] J. Kim and S. Lee, “Deep learning of human visual sensitivity in image quality assessment framework,” in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 1969–1977.

[14] S. Ahn, Y. Choi, and K. Yoon, “Deep learning-based distortion sensitivity prediction for full-reference image quality assessment,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, June 2021, pp. 344–353.

[15] W. Kim, J. Kim, S. Ahn, J. Kim, and S. Lee, “Deep video quality assessor: From spatio-temporal visual sensitivity to a convolutional neural aggregation network,” in *ECCV*, 2018.

[16] M. Xu, J. Chen, H. Wang, S. Liu, G. Li, and Z. Bai, “C3dvqa: Full-reference video quality assessment with 3d convolutional neural network,” in *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020, pp. 4447–4451.

[17] J. Chen, H. Wang, M. Xu, G. Li, and S. Liu, “Deep neural networks for end-to-end spatiotemporal video quality prediction and aggregation,” in *2021 IEEE International Conference on Multimedia and Expo (ICME)*, 2021, pp. 1–6.

[18] D. Ramsook, A. Kokaram, N. O’Connor, N. Birkbeck, Y. Su, and B. Adsumilli, “A differentiable estimator of vmaf for video,” in *2021 Picture Coding Symposium (PCS)*, 2021, pp. 1–5.

[19] L.-H. Chen, C. G. Bampis, Z. Li, A. Norkin, and A. C. Bovik, “Proxiqa: A proxy approach to perceptual optimization of learned image compression,” *IEEE Transactions on Image Processing*, vol. 30, p. 360–373, 2021. [Online]. Available: http://dx.doi.org/10.1109/TIP.2020.3036752

[20] D. Ramsook, A. Kokaram, N. O’Connor, N. Birkbeck, Y. Su, and B. Adsumilli, “A differentiable vmaf proxy as a loss function for video noise reduction,” in *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, vol. 11842, 2021, p. 118420X.

[21] D. Ma, F. Zhang, and D. Bull, “BVI-DVC: a training database for deep video compression,” *IEEE Transactions on Multimedia*, 2021.

[22] I. Katsevounidis, “Dynamic optimizer – a perceptual video encoding optimization framework,” *The Netflix Tech Blog*, 2018.

[23] K. Sharman and K. Suehring, “Common test conditions for hm video quality assessment of natural videos,” *IEEE Transactions on Image Processing*, vol. 19, no. 2, pp. 335–350, 2010.