

# Multi-Frame Quality Enhancement for Compressed Video

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## Abstract

The past few years have witnessed great success in applying deep learning to enhance the quality of compressed image/video. The existing approaches mainly focus on enhancing the quality of a single frame, ignoring the similarity between consecutive frames. In this paper, we investigate that heavy quality fluctuation exists across compressed video frames, and thus low quality frames can be enhanced using the neighboring high quality frames, seen as Multi-Frame Quality Enhancement (MFQE). Accordingly, this paper proposes an MFQE approach for compressed video, as a first attempt in this direction. In our approach, we firstly develop a Support Vector Machine (SVM) based detector to locate Peak Quality Frames (PQFs) in compressed video. Then, a novel Multi-Frame Convolutional Neural Network (MF-CNN) is designed to enhance the quality of compressed video, in which the non-PQF and its nearest two PQFs are as the input. The MF-CNN compensates motion between the non-PQF and PQFs through the Motion Compensation subnet (MC-subnet). Subsequently, the Quality Enhancement subnet (QE-subnet) reduces compression artifacts of the non-PQF with the help of its nearest PQFs. Finally, the experiments validate the effectiveness and generality of our MFQE approach in advancing the state-of-the-art quality enhancement of compressed video. The code of our MFQE approach is available at <https://github.com/ryangBUAA/MFQE.git>.

## 1. Introduction

During the past decades, video has become significantly popular over the Internet. According to the Cisco Data Traffic Forecast [7], video generates 60% of Internet traffic in 2016, and this figure is predicted to reach 78% by 2020. When transmitting video over the bandwidth-limited Internet, video compression has to be applied to significantly save the coding bit-rate. However, the compressed video inevitably suffers from compression artifacts, which may severely degrade the Quality of Experience (QoE). Therefore, it is necessary to study on quality enhancement for

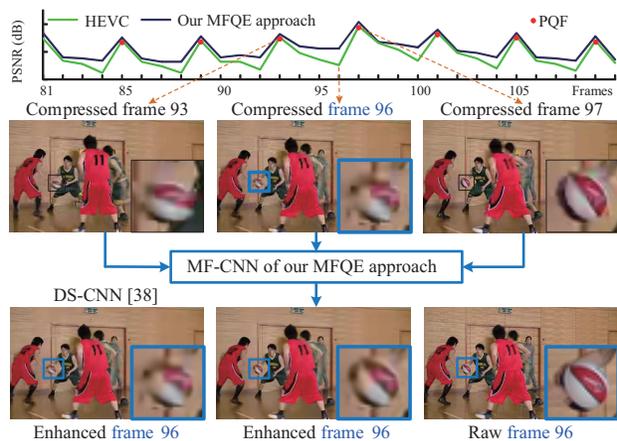


Figure 1. Example for quality fluctuation (top) and quality enhancement performance (bottom).

compressed video.

Recently, there has been increasing interest in enhancing the visual quality of compressed image/video [25, 10, 18, 33, 6, 9, 35, 12, 24, 24, 38]. For example, Dong *et al.* [9] designed a four-layer Convolutional Neural Network (CNN) [22], named AR-CNN, which considerably improves the quality of JPEG images. Later, Yang *et al.* designed a Decoder-side Scalable CNN (DS-CNN) for video quality enhancement [38, 39]. However, when processing a single frame, all existing quality enhancement approaches do not take any advantage of information in the neighbouring frames, and thus their performance is largely limited. As Figure 1 shows, the quality of compressed video dramatically fluctuates across frames. Therefore, it is possible to use the high quality frames (i.e., Peak Quality Frames, called PQFs<sup>1</sup>) to enhance the quality of their neighboring low quality frames (non-PQFs). This can be seen as Multi-Frame Quality Enhancement (MFQE), similar to multi-frame super-resolution [20, 3].

This paper proposes an MFQE approach for compressed video. Specifically, we first investigate that there exists large quality fluctuation across frames, for video sequences compressed by almost all coding standards. Thus, it is nec-

<sup>1</sup>PQFs are defined as the frames whose quality is higher than their previous and subsequent frames.

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essary to find PQFs that can be used to enhance the quality of their adjacent non-PQFs. To this end, we train a Support Vector Machine (SVM) as a no-reference method to detect PQFs. Then, a novel Multi-Frame CNN (MF-CNN) architecture is proposed for quality enhancement, in which both the current frame and its adjacent PQFs are as the inputs. Our MF-CNN includes two components, i.e., Motion Compensation subnet (MC-subnet) and Quality Enhancement subnet (QE-subnet). The MC-subnet is developed to compensate the motion between the current non-PQF and its adjacent PQFs. The QE-subnet, with a spatio-temporal architecture, is designed to extract and merge the features of the current non-PQF and the compensated PQFs. Finally, the quality of the current non-PQF can be enhanced by QE-subnet that takes advantage of the high quality content in the adjacent PQFs. For example, as shown in Figure 1, the current non-PQF (frame 96) and the nearest PQFs (frames 93 and 97) are fed in to the MF-CNN of our MFQE approach. As a result, the low quality content (basketball) of the non-PQF (frame 96) can be enhanced upon the same content but with high quality in the neighboring PQFs (frames 93 and 97). Moreover, Figure 1 shows that our MFQE approach also mitigates the quality fluctuation, because of the considerable quality improvement of non-PQFs.

The main contributions of this paper are: (1) We analyze the frame-level quality fluctuation of video sequences compressed by various video coding standards. (2) We propose a novel CNN-based MFQE approach, which can reduce the compression artifacts of non-PQFs by making use of the neighboring PQFs.

## 2. Related works

**Quality enhancement.** Recently, extensive works [25, 10, 33, 18, 19, 6, 9, 12, 35, 24, 4] have focused on enhancing the visual quality of compressed image. Specifically, Foi *et al.* [10] applied pointwise Shape-Adaptive DCT (SA-DCT) to reduce the blocking and ringing effects caused by JPEG compression. Later, Jancsary *et al.* [18] proposed reducing JPEG image blocking effects by adopting Regression Tree Fields (RTF). Moreover, sparse coding was utilized to remove the JPEG artifacts, such as [19] and [6]. Recently, deep learning has also been successfully applied to improve the visual quality of compressed image. Particularly, Dong *et al.* [9] proposed a four-layer AR-CNN to reduce the JPEG artifacts of images. Afterwards,  $\mathbf{D}^3$  [35] and Deep Dual-domain Convolutional Network (DDCN) [12] were proposed as advanced deep networks for the quality enhancement of JPEG image, utilizing the prior knowledge of JPEG compression. Later, DnCNN was proposed in [40] for several tasks of image restoration, including quality enhancement. Most recently, Li *et al.* [24] proposed a 20-layer CNN, achieving the state-of-the-art quality enhancement performance for compressed image.

For the quality enhancement of compressed video, the

Variable-filter-size Residue-learning CNN (VRCNN) [8] was proposed to replace the inloop filters for HEVC intra-coding. However, the CNN in [8] was designed as a component of the video encoder, so that it is not practical for already compressed video. Most recently, a Deep CNN-based Auto Decoder (DCAD), which contains 10 CNN layers, was proposed in [34] to reduce the distortion of compressed video. Moreover, Yang *et al.* [38] proposed the DS-CNN approach for video quality enhancement. In [38], DS-CNN-I and DS-CNN-B, as two subnetworks of DS-CNN, are used to reduce the artifacts of intra- and inter-coding, respectively. More importantly, the video encoder does not need to be modified when applying the DCAD [34] and DS-CNN [38] approaches. Nevertheless, all above approaches can be seen as single-frame quality enhancement approaches, as they do not use any advantageous information available in the neighboring frames. Consequently, the video quality enhancement performance is severely limited.

**Multi-frame super-resolution.** To our best knowledge, there exists no MFQE work for compressed video. The closest area is multi-frame video super-resolution. In the early years, Brandi *et al.* [2] and Song *et al.* [30] proposed to enlarge video resolution by taking advantage of high resolution key-frames. Recently, many multi-frame super-resolution approaches have employed deep neural networks. For example, Huang *et al.* [17] developed a Bidirectional Recurrent Convolutional Network (BRCN), which improves the super-resolution performance over traditional single-frame approaches. In 2016, Kappeler *et al.* proposed a Video Super-Resolution network (VSRnet) [20], in which the neighboring frames are warped according to the estimated motion, and both the current and warped neighboring frames are fed into a super-resolution CNN to enlarge the resolution of the current frame. Later, Li *et al.* [23] proposed replacing VSRnet by a deeper network with residual learning strategy. Besides, other deep learning approaches of video super-resolution were proposed in [26, 3].

The aforementioned multi-frame super-resolution approaches are motivated by the fact that different observations of the same objects or scenes are probably available across frames of a video. As a result, the neighboring frames may contain the content missed when down-sampling the current frame. Similarly, for compressed video, the low quality frames can be enhanced by taking advantage of their adjacent higher quality frames, because heavy quality fluctuation exists across compressed frames. Consequently, the quality of compressed video may be effectively improved by leveraging the multi-frame information. To the best of our knowledge, our MFQE approach proposed in this paper is the first attempt in this direction.

## 3. Quality fluctuation of compressed video

In this section, we analyze the quality fluctuation of compressed video alongside the frames. First, we establish a

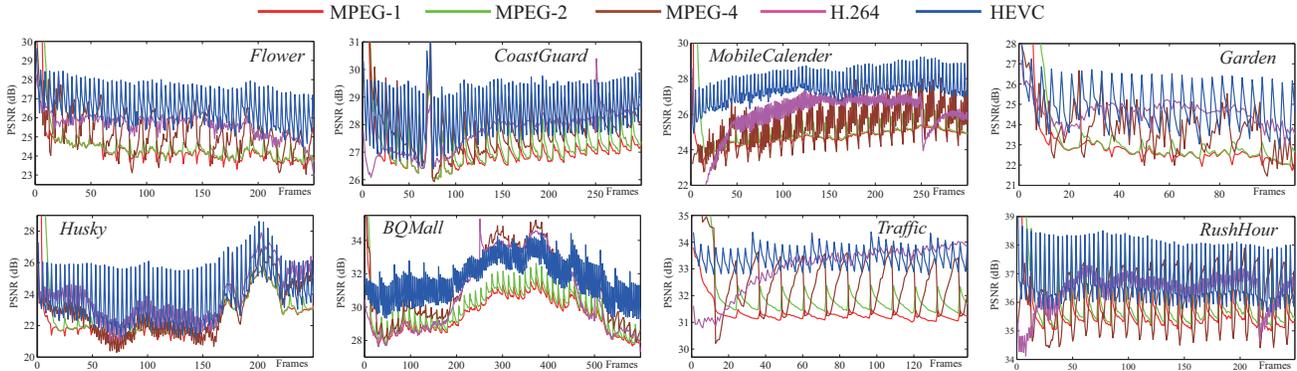


Figure 2. PSNR curves of compressed video for various compression standards.

database including 70 uncompressed video sequences, selected from the datasets of Xiph.org [37] and JCT-VC [1]. We compress these sequences using various video coding standards, including MPEG-1 [11], MPEG-2 [28], MPEG-4 [29], H.264/AVC [36] and HEVC [31]. The quality of each compressed frame is evaluated in terms of Peak Signal-to-Noise Ratio (PSNR).

Figure 2 shows the PSNR curves of 8 video sequences, which are compressed by different standards. It can be seen that the compression quality obviously fluctuates along with the frames. We further measure the Standard Deviation (STD) of frame-level quality for each compressed video. As shown in Table 1, the STD values of all five standards are above 1.00 dB, which are averaged over the 70 compressed sequences. The maximal STD among the 70 sequences reaches 3.97 dB, 4.00 dB, 3.84 dB, 5.67 dB and 3.34 dB for MPEG-1, MPEG-2, MPEG-4, H.264 and HEVC, respectively. This reflects the remarkable fluctuation of frame-level quality after video compression.

Moreover, Figure 3 shows an example of the frame-level PSNR and subjective quality for one sequence, compressed by the latest HEVC standard. It can be observed from Figure 3 that there exists frequently alternate PQFs and Valley Quality Frames (VQFs). Here, PQF is defined as the frame whose quality is higher than its previous and subsequent frames. In contrast, VQF indicates the frame with lower quality than its previous and subsequent frames. As shown in this figure, the PSNR of non-PQFs (frames 58-60), especially the VQF (frame 60), is obviously lower than that of the nearest PQFs (frames 57 and 61). Moreover, non-PQFs (frames 58-60) also have much lower subjective quality than the nearest PQFs (frames 57 and 61), e.g., in the region of number “87”. Additionally, the content of frames 57-61 is very similar. Hence, the visual quality of non-PQFs can be improved by using the content in the nearest PQFs.

To further analyze the peaks and valleys of frame-level quality, we measure the Peak-Valley Difference (PVD) and Peak Separation (PS) for the PSNR curves of each compressed video sequence. As seen in Figure 3-(a), PVD is denoted as the PSNR difference between the PQF and its n-

Table 1. Averaged STD, PVD and PS values among our database.

	MPEG-1	MPEG-2	MPEG-4	H.264	HEVC
STD (dB)	1.8336	1.8347	1.7823	1.6370	1.0566
PVD (dB)	1.1072	1.1041	1.0420	0.5275	1.5089
PS (frame)	5.3438	5.3630	5.3819	1.6365	2.6600

earliest VQF, and PS indicates the number of frames between two PQFs. The averaged PVD and PS values of the 70 compressed video sequences are shown in Table 1 for each video coding standard. It can be seen that the averaged PVD values are higher than 1.00 dB in most cases, and the latest HEVC standard has the highest value of 1.50 dB. This verifies the large quality difference between PQFs and VQFs. Additionally, the PS values are approximately or less than 5 frames for each coding standard. In particular, the PS values are less than 3 frames for the H.264 and HEVC standards. Such a short distance between two PQFs indicates that the content of frames between the adjacent PQFs may be highly similar. Therefore, the PQFs probably contain some useful content which is distorted in their neighboring non-PQFs. Motivated by this, our MFQE approach is proposed to enhance the quality of non-PQFs through the advantageous information of the nearest PQFs.

## 4. The proposed MF-CNN approach

### 4.1. Framework

Figure 4 shows the framework of our MFQE approach. In the MFQE approach, we first detect the PQFs that are used for quality enhancement of other non-PQFs. In practical application, the raw sequences are not available in video quality enhancement, and thus the PQFs and non-PQFs cannot be distinguished through comparison with the raw sequences. Therefore, we develop a no-reference PQF detector in our MFQE approach, which is detailed in Section 4.2.

The quality of detected PQFs can be enhanced by DS-CNN [38], which is a single-frame approach for video quality enhancement. It is because the adjacent frames of a PQF are with lower quality and cannot benefit the quality enhancement of this PQF. Here, we modify the DS-CNN via replacing the Rectified Linear Units (ReLU) by Parametric ReLU (PReLU) to avoid zero gradients [14], and we also

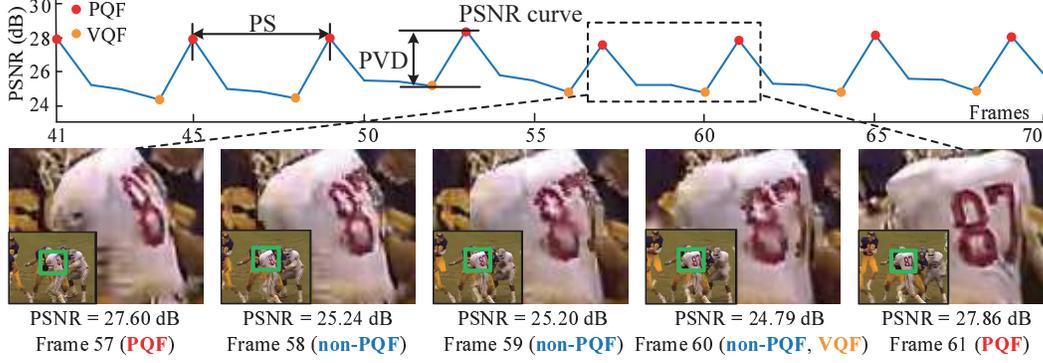


Figure 3. Example of the frame-level PSNR and subjective quality for the HEVC compressed video sequence *Football*.

apply residual learning [13] to improve the quality enhancement performance.

For non-PQFs, the MF-CNN is proposed to enhance the quality that takes advantage of the nearest PQFs (i.e., both previous and subsequent PQFs). The MF-CNN architecture is composed of the MC-subnet and the QE-subnet. The MC-subnet is developed to compensate the temporal motion across the neighboring frames. To be specific, the MC-subnet firstly predicts the temporal motion between the current non-PQF and its nearest PQFs. Then, the two nearest PQFs are warped with the spatial transformer according to the estimated motion. As such, the temporal motion between the non-PQF and PQFs can be compensated. The MC-subnet is to be introduced in Section 4.3.

Finally, the QE-subnet, which has a spatio-temporal architecture, is proposed for quality enhancement, as introduced in Section 4.4. In the QE-subnet, both the current non-PQF and the compensated PQFs are as the inputs, and then the quality of the current non-PQF can be enhanced under the help of the adjacent compensated PQFs. Note that, in the proposed MF-CNN, the MC-subnet and QE-subnet are trained jointly in an end-to-end manner.

## 4.2. SVM-based PQF detector

In our MFQE approach, an SVM classifier is trained to achieve no-reference PQF detection. Recall that PQF is the frame with higher quality than the adjacent frames. Thus both the features of the current and four neighboring frames are used to detect PQFs. In our approach, the PQF detector follows the no-reference quality assessment method [27] to extract 36 spatial features from the current frame, each of which is one-dimensional. Beyond, such kinds of spatial features are also extracted from two previous frames and two incoming frames. Consequently, 180 one-dimensional features are obtained to predict whether a frame is a PQF or non-PQF, based on the SVM classifier.

In our SVM classifier,  $l_n \in \{0, 1\}$  denotes the output class label indicating whether the  $n$ -th frame is a PQF (positive sample with  $l_n = 1$ ) or non-PQF (negative sample with  $l_n = 0$ ). We use the LIBSVM library [5] to train the SVM

classifier, in which the probability of  $l_n = 1$  can be obtained for each frame and denoted as  $p_n$ . In our SVM classifier, the Radial Basis Function (RBF) is used as the kernel.

Finally,  $\{l_n, p_n\}_{n=1}^N$  can be obtained from the SVM classifier, in which  $N$  is the total number of frames in the video sequence. In our PQF detector, we further refine the results of the SVM classifier according to the prior knowledge of PQF. Specifically, the following two strategies are developed to refine the labels  $\{l_n\}_{n=1}^N$  of the PQF detector.

(1) According to the definition of PQF, it is impossible that the PQFs consecutively appear. Hence, if the following case exists

$$\{l_{n+i}\}_{i=0}^j = 1 \quad \text{and} \quad l_{n-1} = l_{n+j+1} = 0, \quad j \geq 1, \quad (1)$$

we set

$$l_{n+i} = 0, \quad \text{where} \quad i \neq \arg \max_{0 \leq k \leq j} (p_{n+k}) \quad (2)$$

in our PQF detector.

(2) According to the analysis of Section 3, PQFs frequently appear within a limited separation. For example, the average value of PS is 2.66 frames for HEVC compressed sequences. Here, we assume that  $D$  is the maximal separation between two PQFs. Given this assumption, if the results of  $\{l_n\}_{n=1}^N$  yields more than  $D$  consecutive zeros (non-PQFs):

$$\{l_{n+i}\}_{i=0}^d = 0 \quad \text{and} \quad l_{n-1} = l_{n+d+1} = 1, \quad d > D, \quad (3)$$

one of frames need to be selected as PQF, and thus we set

$$l_{n+i} = 1, \quad \text{where} \quad i = \arg \max_{0 < k < d} (p_{n+k}). \quad (4)$$

After refining  $\{l_n\}_{n=1}^N$  as discussed above, our PQF detector can locate PQFs and non-PQFs in the compressed video.

## 4.3. MC-subnet

After PQFs are detected, the quality of non-PQFs can be enhanced by taking advantage of the neighboring PQFs. However, the temporal motion exists between non-PQFs

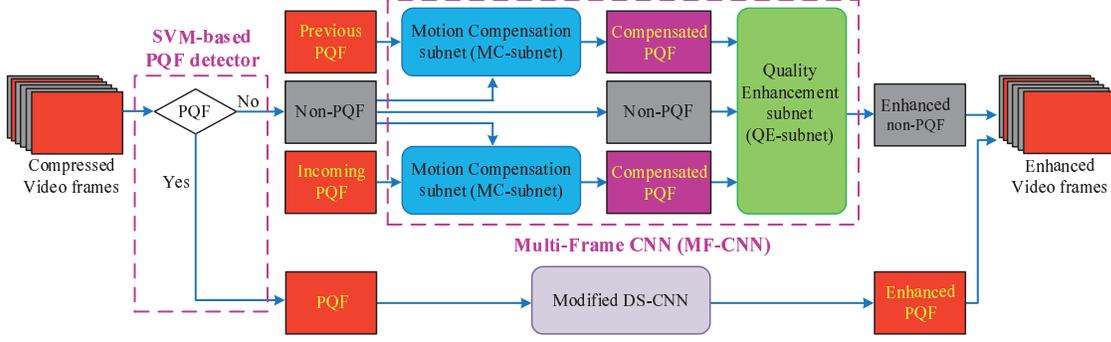


Figure 4. Framework of the proposed MFQE approach.

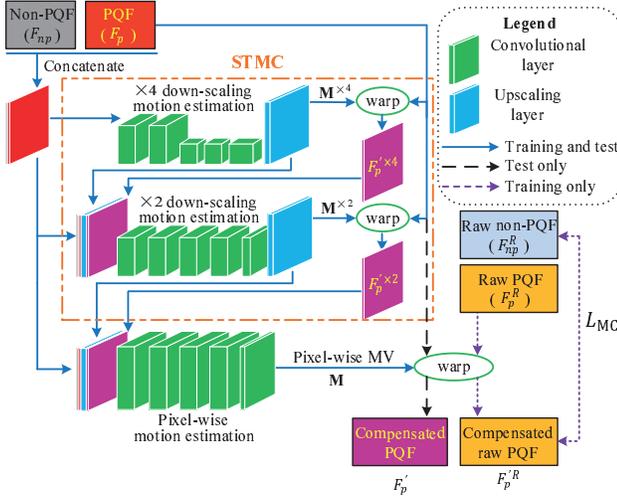


Figure 5. Architecture of our MC-subnet.

Table 2. Convolutional layers for pixel-wise motion estimation.

Layers	Conv 1	Conv 2	Conv 3	Conv 4	Conv 5
Filter size	$3 \times 3$				
Filter number	24	24	24	24	2
Stride	1	1	1	1	1
Function	PRReLU	PRReLU	PRReLU	PRReLU	Tanh

and PQFs. Hence, we develop the MC-subnet to compensate the temporal motion across frames. In the following, the architecture and training strategy of our MC-subnet are introduced in detail.

**Architecture.** In [3], Caballero *et al.* proposed the Spatial Transformer Motion Compensation (STMC) method for multi-frame super-resolution. As shown in Figure 5, the STMC method adopts the convolutional layers to estimate the  $\times 4$  and  $\times 2$  down-scaling Motion Vector (MV) maps, denoted as  $M^{\times 4}$  and  $M^{\times 2}$ . In  $M^{\times 4}$  and  $M^{\times 2}$ , the down-scaling is achieved by adopting some convolutional layers with the stride of 2. For details of these convolutional layers, refer to [3].

The down-scaling motion estimation is effective to handle large scale motion. However, because of down-scaling, the accuracy of MV estimation is reduced. Therefore, in addition to STMC, we further develop some additional convolutional layers for pixel-wise motion estimation in our MC-

subnet, which does not contain any down-scaling process. The convolutional layers of pixel-wise motion estimation are described in Table 2. As Figure 5 shows, the output of STMC includes the  $\times 2$  down-scaling MV map  $M^{\times 2}$  and the corresponding compensated PQF  $F_p^{\times 2}$ . They are concatenated with the original PQF and non-PQF, as the input to the convolutional layers of the pixel-wise motion estimation. Then, the pixel-wise MV map can be generated, which is denoted as  $M$ . Note that the MV map  $M$  contains two channels, i.e., horizontal MV map  $M_x$  and vertical MV map  $M_y$ . Here,  $x$  and  $y$  are the horizontal and vertical index of each pixel. Given  $M_x$  and  $M_y$ , the PQF is warped to compensate the temporal motion. Let the compressed PQF and non-PQF be  $F_p$  and  $F_{np}$ , respectively. The compensated PQF  $F_p'$  can be expressed as

$$F_p'(x, y) = \mathcal{I}\{F_p(x + M_x(x, y), y + M_y(x, y))\}, \quad (5)$$

where  $\mathcal{I}\{\cdot\}$  means the bilinear interpolation. The reason for the interpolation is that  $M_x(x, y)$  and  $M_y(x, y)$  may be non-integer values.

**Training strategy.** Since it is hard to obtain the ground truth of MV, the parameters of the convolutional layers for motion estimation cannot be trained directly. The super-resolution work [3] trains the parameters by minimizing the MSE between the compensated adjacent frame and the current frame. However, in our MC-subnet, both the input  $F_p$  and  $F_{np}$  are compressed frames with quality distortion. Hence, when minimizing the MSE between  $F_p'$  and the  $F_{np}$ , the MC-subnet learns to estimate the distorted MV, resulting in inaccurate motion estimation. Therefore, the MC-subnet is trained under the supervision of the raw frames. That is, we warp the raw frame of the PQF (denoted as  $F_p^R$ ) using the MV map output from the convolutional layers of motion estimation, and minimize the MSE between the compensated raw PQF (denoted as  $F_p^{R'}$ ) and the raw non-PQF (denoted as  $F_{np}^R$ ). The loss function of the MC-subnet can be written by

$$L_{MC}(\theta_{mc}) = \|F_p^{R'}(\theta_{mc}) - F_{np}^R\|_2^2, \quad (6)$$

where  $\theta_{mc}$  represents the trainable parameters of our MC-

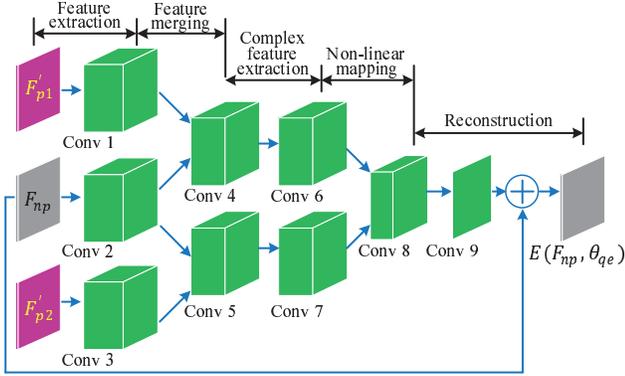


Figure 6. Architecture of our QE-subnet.

Table 3. Convolutional layers of our QE-subnet.

Layers	Conv 1/2/3	Conv 4/5	Conv 6/7	Conv 8	Conv 9
Filter size	$9 \times 9$	$7 \times 7$	$3 \times 3$	$1 \times 1$	$5 \times 5$
Filter number	128	64	64	32	1
Stride	1	1	1	1	1
Function	PRReLU	PRReLU	PRReLU	PRReLU	—

subnet. Note that the raw frames  $F_p^R$  and  $F_{np}^R$  are not required when compensating motion in the test.

#### 4.4. QE-subnet

Given the compensated PQFs, the quality of non-PQFs can be enhanced through the QE-subnet, which is designed with spatio-temporal architecture. Specifically, together with the current processed non-PQF  $F_{np}$ , the compensated previous and subsequent PQFs (denoted by  $F'_{p1}$  and  $F'_{p2}$ ) are input to the QE-subnet. This way, both the spatial and temporal features of these three frames are explored and merged. Consequently, the advantageous information in the adjacent PQFs can be used to enhance the quality of the non-PQF. It differs from the CNN-based image/single-frame quality enhancement approaches, which only handle the spatial information within one frame.

**Architecture.** The architecture of the QE-subnet is shown in Figure 6, and the details of the convolutional layers are presented in Table 3. In the QE-subnet, the convolutional layers Conv 1, 2 and 3 are applied to extract the spatial features of input frames  $F'_{p1}$ ,  $F_{np}$  and  $F'_{p2}$ , respectively. Then, in order to use the high quality information of  $F'_{p1}$ , Conv 4 is adopted to merge the features of  $F_{np}$  and  $F'_{p1}$ . That is, the outputs of Conv 1 and 2 are concatenated and then convolved by Conv 4. Similarly, Conv 5 is used to merge the features of  $F_{np}$  and  $F'_{p2}$ . Conv 6/7 is designed to extract more complex features from Conv 4/5. Consequently, the extracted features of Conv 6 and Conv 7 are non-linearly mapped to another space through Conv 8. Finally, the reconstructed residual, denoted as  $R_{np}(\theta_{qe})$ , is achieved in Conv 9, and the non-PQF is enhanced by adding  $R_{np}(\theta_{qe})$  to the input non-PQF  $F_{np}$ . Here,  $\theta_{qe}$  is defined as the trainable parameters of QE-subnet.

**Training strategy.** The MC-subnet and QE-subnet of our MF-CNN are trained jointly in an end-to-end manner.

Assume that  $F_{p1}^R$  and  $F_{p2}^R$  are defined as the raw frames of the previous and incoming PQFs, respectively. The loss function of our MF-CNN can be formulated as

$$L_{MF}(\theta_{mc}, \theta_{qe}) = a \cdot \underbrace{\sum_{i=1}^2 \|F_{pi}^R(\theta_{mc}) - F_{np}^R\|_2^2}_{L_{MC}: \text{loss of MC-subnet}} + b \cdot \underbrace{\|(F_{np} + R_{np}(\theta_{qe})) - F_{np}^R\|_2^2}_{L_{QE}: \text{loss of QE-subnet}}. \quad (7)$$

As (7) indicates, the loss function of the MF-CNN is the weighted sum of  $L_{MC}$  and  $L_{QE}$ , which are the loss functions of MC-subnet and QE-subnet, respectively. Because  $F'_{p1}$  and  $F'_{p2}$  generated by the MC-subnet are the basis of the following QE-subnet, we set  $a \gg b$  at the beginning of training. After the convergence of  $L_{MC}$  is observed, we set  $a \ll b$  to minimize the MSE between  $F_{np} + R_{np}$  and  $F_{np}^R$ . As a result, the quality of non-PQF  $F_{np}$  can be enhanced by using the high quality information of its nearest PQFs.

## 5. Experiments

### 5.1. Settings

The experimental results are presented to validate the effectiveness of our MFQE approach. In our experiments, all 70 video sequences of our database introduced in Section 3 are randomly divided into the training set (60 sequences) and the test set (10 sequences). The training and test sequences are compressed by the latest HEVC standard, setting the Quantization Parameter (QP) to 42 and 37. We train two models of our MFQE approach for the sequences compressed at QP = 37 and 42, respectively. In the SVM-based PQF detector, the parameter  $D^2$  is set to 6 in (3). It is because the maximal separation between two nearest PQFs is 6 frames in all training sequences compressed by HEVC. When training the MF-CNN, the raw and compressed sequences are segmented into  $64 \times 64$  patches as the training samples. The batch size is set to 64. We adopt the Adam algorithm [21] with initial learning rate as  $10^{-4}$  to minimize the loss function of (7). In the training stage, we initially set  $a = 1$  and  $b = 0.01$  of (7) to train the MC-subnet. After the MC-subnet converges, these hyperparameters are set as  $a = 0.01$  and  $b = 1$  to train the QE-subnet.

### 5.2. Performance of the PQF detector

Because PQF detection is the first stage of the proposed MFQE approach, the performance of our PQF detector is evaluated in terms of precision, recall and  $F_1$ -score, as shown in Table 4. We can see from Table 4 that at QP = 37, the average precision and recall of our SVM-based PQF detector are 90.68% and 92.11%, respectively. In addition,

<sup>2</sup> $D$  should be changed according to coding standard and configurations.

Table 4. Performance of the PQF detector on the test sequences.

Method	QP	Precision	Recall	$F_1$ -score
Our SVM-based	37	<b>90.68%</b>	<b>92.11%</b>	<b>91.09%</b>
PQF detector	42	<b>93.98%</b>	<b>90.86%</b>	<b>92.23%</b>

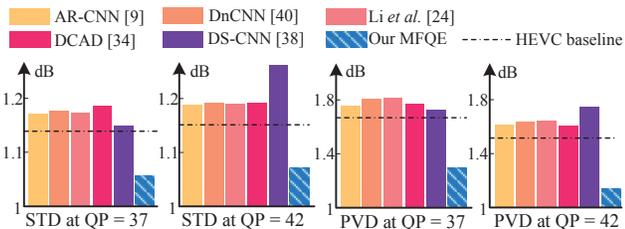


Figure 7. Averaged STD and PVD values of the test sequences.

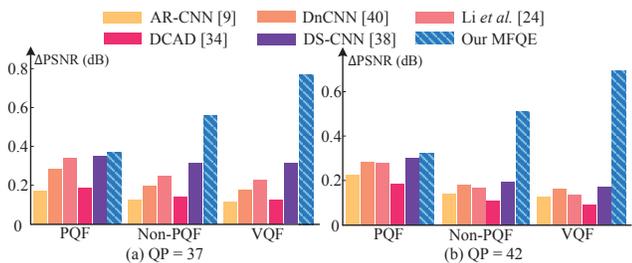


Figure 8.  $\Delta$ PSNR (dB) on PQFs, non-PQFs and VQFs of the test sequences.

the  $F_1$ -score, which is defined as the harmonic average of the precision and the recall, is 91.09% on average. Similar results can be found for all test sequences compressed at QP = 42, in which the average precision, recall and  $F_1$ -score are 93.98%, 90.86% and 92.23%, respectively. Thus, the effectiveness of our SVM-based PQF detector is validated.

### 5.3. Performance of our MFQE approach

In this section, we evaluate the quality enhancement performance of our MFQE approach in terms of  $\Delta$ PSNR, which measures the PSNR difference between the enhanced and the original compressed sequence. Our performance is compared with AR-CNN [9], DnCNN [40], Li *et al.* [24]<sup>3</sup>, DCAD [34] and DS-CNN [38]. Among them, AR-CNN, DnCNN and Li *et al.* are the latest quality enhancement approaches for compressed image. DCAD and DS-CNN are the state-of-the-art video quality enhancement approaches.

**Quality enhancement on non-PQFs.** Our MFQE approach mainly focuses on enhancing the quality of non-PQFs using the multi-frame information. Therefore, we first assess the quality enhancement of non-PQFs. Figure 8 shows the  $\Delta$ PSNR results averaged over PQFs, non-PQFs and VQFs of all 10 test sequences, compressed at QP = 37. As shown in this figure, our MFQE approach has a considerably larger PSNR improvement for non-PQFs, compared to that for PQFs. Furthermore, an even higher  $\Delta$ PSNR can be achieved for VQFs in our approach. In contrast, for compared approaches, the PSNR improvement of non-PQFs is

<sup>3</sup>Note that AR-CNN [9], DnCNN [40] and Li *et al.* [24] are re-trained on HEVC compressed samples for fair comparison.

Table 5. Overall  $\Delta$ PSNR (dB) of the test sequences.

QP	Seq.	AR-CNN [9]	DnCNN [40]	Li <i>et al.</i> [24]	DCAD [34]	DS-CNN [38]	MFQE (our)
37	1	0.1287	0.1955	0.2523	0.1354	0.4762	<b>0.7716</b>
	2	0.0718	0.1888	0.2857	0.0376	0.4228	<b>0.6042</b>
	3	0.1095	0.1328	0.1872	0.1112	0.2394	<b>0.4715</b>
	4	0.1304	0.2084	0.2170	0.0796	0.3173	<b>0.4381</b>
	5	0.1900	0.2936	0.3645	0.2334	0.3252	<b>0.5496</b>
	6	0.1522	0.1944	0.2630	0.1619	0.3728	<b>0.5980</b>
	7	0.1445	0.2224	0.2570	0.1775	0.2777	<b>0.3898</b>
	8	0.1305	0.2424	0.2939	0.1940	0.2790	<b>0.4838</b>
	9	0.1573	0.2588	0.3034	0.2224	0.2720	<b>0.3935</b>
	10	0.1490	0.2509	0.2926	0.2026	0.2498	<b>0.4019</b>
	Ave.	0.1364	0.2188	0.2717	0.1556	0.3232	<b>0.5102</b>
42	Ave.	0.1627	0.2073	0.1924	0.1282	0.2189	<b>0.4610</b>

1: PeopleOnStreet 2: TunnelFlag 3: Kimono 4: BarScene 5: Vidyo1 6: Vidyo3 7: Vidyo4 8: BasketballPass 9: RaceHorses 10: MaD

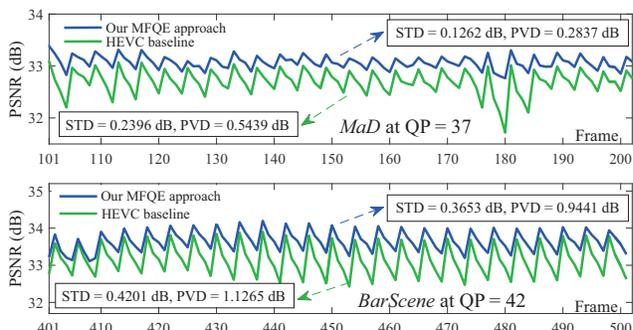


Figure 9. PSNR curves of HEVC and our MFQE approach.

similar to or even less than that of PQFs. Specifically, for non-PQFs, our MFQE approach doubles  $\Delta$ PSNR of DS-CNN [38], which performs best among all of the compared approaches. This validates the effectiveness of our MFQE approach in enhancing the quality of non-PQFs.

**Overall quality enhancement.** Table 5 presents the  $\Delta$ PSNR results averaged over all frames, for each test sequence. As this table shows, our MFQE approach outperforms all five compared approaches for all test sequences. To be specific, at QP = 37, the highest  $\Delta$ PSNR of our MFQE approach reaches 0.7716 dB. The averaged  $\Delta$ PSNR of our MFQE approach is 0.5102 dB, which is 87.78% higher than that of Li *et al.* [24] (0.2717 dB), and 57.86% higher than that of DS-CNN (0.3233 dB). Besides, more  $\Delta$ PSNR gain can be obtained in our MFQE approach, when compared with AR-CNN [9], DnCNN [40] and DCAD [34]. At QP = 42, our MFQE approach ( $\Delta$ PSNR = 0.4610 dB) also doubles the PSNR improvement of the second best approach DS-CNN ( $\Delta$ PSNR = 0.2189 dB). Thus, our MFQE approach is effective in overall quality enhancement. This is mainly due to the large improvement in non-PQFs, which are the majority of compressed video frames.

**Quality fluctuation.** Apart from the artifacts, the quality fluctuation of compressed video may also lead to degradation of QoE [15, 32, 16]. Fortunately, as discussed above, our MFQE approach is able to mitigate the quality fluctuation, because of the higher PSNR improvement of non-PQFs. We evaluate the fluctuation of video quality in terms of the STD and PVD of the PSNR curve, as introduced in Section 3. Figure 7 shows the STD and PVD values av-

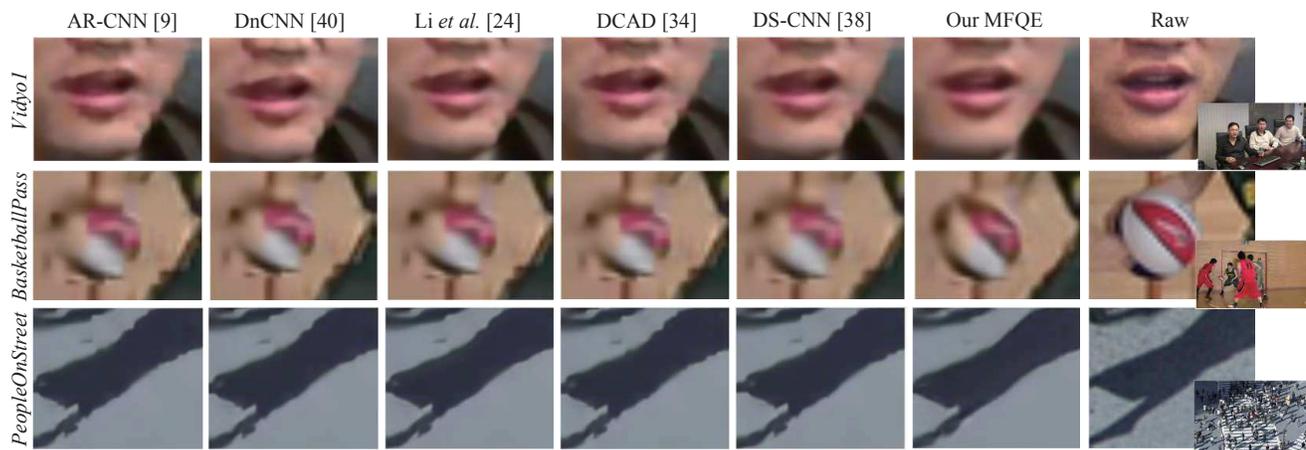


Figure 10. Subjective quality performance on *Vidyo1* at QP = 37, *BasketballPass* at QP = 37 and *PeopleOnStreet* at QP = 42.

eraged over all test sequences, for the HEVC baseline and the quality enhancement approaches. As shown in this figure, our MFQE approach succeeds in reducing the STD and PVD after enhancing the quality of the compressed sequences. By contrast, the five compared approaches enlarge the STD and PVD values over the HEVC baseline. Thus, our MFQE approach is able to mitigate the quality fluctuation and achieve better QoE, compared with other approaches. Figure 9 further shows the PSNR curves of the HEVC baseline and our MFQE approach for two test sequences. It can be seen that the PSNR fluctuation of our MFQE approach is obviously less than the HEVC baseline. To summarize, our MFQE approach is effective to mitigate the quality fluctuation of compressed video, meanwhile enhancing video quality.

**Subjective quality performance.** Figure 10 shows the subjective quality performance on the sequences *Vidyo1* at QP = 37, *BasketballPass* at QP = 37 and *PeopleOnStreet* at QP = 42. One may observe from Figure 10 that our MFQE approach reduces the compression artifacts more effectively than the five compared approaches. Specifically, the severely distorted content, e.g., the mouth in *Vidyo1*, the ball in *BasketballPass* and the shadow in *PeopleOnStreet*, can be finely restored in our MFQE approach upon the same content from the neighboring high quality frames. In contrast, such distortion can hardly be restored in the compared approaches, which only use the single low quality frame.

**Effectiveness of utilizing PQFs.** Finally, we validate the effectiveness of utilizing PQFs by re-training our MF-CNN to enhance non-PQFs using adjacent frames instead of PQFs. In our experiments, using adjacent frames instead of PQFs only has 0.3896 dB and 0.3128 dB  $\Delta$ PSNR at QP=37 and 42, respectively. By contrast, as aforementioned, utilizing PQFs achieves  $\Delta$ PSNR = 0.5102 dB and 0.4610 dB at QP = 37 and 42. Moreover, it has been discussed before that non-PQFs, which are enhanced taking advantage of PQFs, have much larger  $\Delta$ PSNR than PQFs. These validate the effectiveness of utilizing PQFs in our MFQE approach.

#### 5.4. Transfer to H.264 standard

We further verify the generalization capability of our MFQE approach by transferring to H.264 compressed sequences. The training and test sequences of our database are compressed by H.264 at QP = 37. Then, the training sequences are used to fine-tune the MF-CNN model. Then, the quality of the test H.264 sequences is improved by our MFQE approach with the fine-tuned MF-CNN model. We find that the average PSNR of test sequences can be increased by 0.4540 dB. This result is comparable to that of HEVC (0.5102 dB). Therefore, the generalization capability of our MFQE approach can be verified.

#### 6. Conclusion

In this paper, we have proposed a CNN-based MFQE approach to reduce compression artifacts of video. Differing from the conventional single frame quality enhancement, our MFQE approach improves the quality of one frame by using high quality content of its nearest PQFs. To this end, we developed an SVM-based PQF detector to classify PQFs and non-PQFs in compressed video. Then, we proposed a novel CNN framework, called MF-CNN, to enhance the quality of each non-PQF. Specifically, the MC-subnet of our MF-CNN compensates motion between PQFs and non-PQFs. Subsequently, the QE-subnet enhances the quality of each non-PQF by inputting the current non-PQF and the nearest compensated PQFs. Finally, experimental results showed that our MFQE approach significantly improves the quality of non-PQFs, far better than other state-of-the-art quality enhancement approaches. Consequently, the overall quality enhancement is considerably higher than other approaches, with less quality fluctuation.

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