VESR-Net: The Winning Solution to Youku Video Enhancement and Super-Resolution Challenge

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Abstract

This paper introduces VESR-Net, a method for video enhancement and super-resolution (VESR). We design a separate non-local module to explore the relations among video frames and fuse video frames efficiently, and a channel attention residual block to capture the relations among feature maps for video frame reconstruction in VESR-Net. We conduct experiments to analyze the effectiveness of these designs in VESR-Net, which demonstrates the advantages of VESR-Net over previous state-of-the-art VESR methods. It is worth to mention that among more than thousands of participants for Youku video enhancement and super-resolution (Youku-VESR) challenge, our proposed VESR-Net beat other competitive methods and ranked the first place.

1. Introduction

Video enhancement and super-resolution (VESR) [7, 5, 22, 11, 19] aims to recover high-resolution details from noisy and low-resolution video frames, and has draw a lot of attention both in the research and industrial community. Recent research on VESR largely focuses on some public datasets [23, 13], which usually use bicubic down-sampling [3] to obtain the low-resolution videos and cannot cover the degradations in industrial scenarios [16, 21]. In order to push the VESR research towards restoring high-quality videos from low-quality videos that suffer from real-world degradations, Youku hosted the video enhancement and super-resolution (Youku-VESR) challenge¹ to explore the VESR solutions on the datasets that cover the realistic degradations in Youku online video watching application².

We introduce our participated solution, VESR-Net, which won the first place in Youku-VESR challenge. Specifically, we design a separate non-local (Separate NL) module to explore the relations among video frames and fuse video frames efficiently, and a channel attention residual block (CARB) [23] to capture the relation among feature maps for video frame reconstruction in VESR-Net. Compared with previous VESR methods [23, 19] that suffer from high computation complexity, VESR-Net is more efficient while more effective.

In the following sections, we first briefly introduce Youku-VESR challenge, and describe the related works on VESR. We then introduce our proposed VESR-Net in details and conduct experimental studies to verify the effectiveness of designs in VESR-Net. We further show the results of VESR-Net in Youku-VESR challenge.

2. Related Work

Video enhancement and super-resolution has attracted more and more research attention in recent years. How to explore the relations between adjacent video frames is essential to achieve good performance. Recently, many progresses of research were made [1, 4, 5, 7, 14, 17, 19]. RCAN [23] is the state-of-the-art algorithm for image super-resolution. [9, 7] proposed 3-dimensional (3D) con-

¹The challenge webside is here: https://tianchi.aliyun.com/competition/entrance/231711/rankingList/1
²https://www.youku.com/
Figure 1. The overview of VESR-Net. We employ both PCD convolution in [19] and separate non-local architecture to aggregate the information among different frames. For reconstruction, we utilize stacked channel-attention residual block (CARB) [23] followed with a feature decoder. The gray arrow denotes the L1 loss applied on the central target frame.

olution neural networks to exploit the spatial and temporal information of video frames simultaneously. Li et al. [9] proposed 3-dimensional (3D) convolution neural networks to exploit the spatial and temporal information of video frames simultaneously. Kim et al. [7] proposed a spatio-temporal network to mitigate occlusions in optical flow estimation. Xue et al. [22] proposed a framework to exploit the temporal relation with the optical flow. Recent methods [4, 14] pay attention to recurrent framework which is efficient to learn the sequential features. Jo et al. [6] designed a dynamic upsampling filters for video super-resolution which are computed depending on the local spatio-temporal neighborhood of each pixel to avoid explicit motion compensation.

However, most algorithms suffer from high computation complexity. For example, RCAN [23] ignores the cross-frame information and needs to stack more than 400 layers to achieve good reconstruction accuracy. EDVR [19] fuses cross-frame information with deformable network and attention mechanism, which still needs to stack 40 residual blocks for final reconstruction. Different from these methods, our method aims to explore the relations among different frames with attention mechanism to improve the information fusion among frames and leverage the residual attention module to improve the frame reconstruction.

3. Youku-VESR Challenge

The objective of the Youku-VESR challenge is to push the state-of-the-art VESR methods towards restoring low-quality videos with realistic degradations. Youku-VESR challenge collects 1000 1080p video clips, with both high-resolution and low-resolution video pairs. This dataset contains diverse contents that cover a variety of categories, and the low-resolution videos suffer from different noises incurred in the online video watching application.

Challenge phases  (i) The first phase: All participants got 200 pairs of low-resolution (LR) and high-resolution (HR) videos for training and 50 LR videos for evaluation. An online validation server with a leaderboard provided accuracy score for the uploaded HR video results corresponding to the LR videos in the evaluation set. (2) The second phase: Youku releases 650 pairs of LR and HR videos for training and 100 LR videos for validation. The LR videos in the second phase suffer from severer degradations than those in the first phase.

Evaluation phases The quantitative metrics are Peak Signal-to-Noise Ratio (PSNR) measured in deciBels [dB] and video multi-method assessment fusion (VMAF) [10]. These metrics are computed between the generated HR results and the ground-truth HR video frames. Each solution will be evaluated on 50 videos provided by Youku. They tested all video frames in top 5 videos and tested one frame in every 5 frames for remaining videos.

4. Methods

In this section, we introduce our method used in Youku-VESR challenge, which is called as VESR-Net.

4.1. VESR-Net

In VESR, the information across frames and across pixels in each frame could be useful for the reconstruction of high-quality frame. However, the disturbing frames need to be ignored by capturing the relation among different frames, due to that scene switching is common among different video frames. We also need to selectively focus on other pixels in the same frame for reconstruction. Therefore, how to fuse the information across video frames and across pixels in each frame is the key to achieve good performance, which has not been exploited well by previous works. Therefore, we propose VESR-Net to enhance the inter-frame and intra-frame fusion for high-quality video frame reconstruction. As shown in Figure 1, VESR-Net consists of two components: a fusion module with inter-frame fusion and a reconstruct module with intra-frame fusion. In the fusion module, we aim to fuse neighboring frames for middle frame reconstruction. In this module, we
explore the useful information from neighboring frames and at the same time ignore the temporal redundancy information. Therefore, we propose a Separate Non-Local (Separate NL) architecture to model the relation among video features. In frame reconstruction module, we introduce channel-wise attention mechanism in residual block (denoted by CARB) for efficient reconstruction. We describe the details of Separate Non-Local (Separate NL) in fusion module and Channel-Attention Residual Block (CARB) in reconstruction module in the following subsections. The detailed configurations of VESR-Net is shown in Table 1.

\[
M_{ij} = \frac{\exp(A^T \cdot B)}{\sum_{i=1}^{N} \exp(A^T \cdot B)}
\]

where \(M_{ij}\) measures the impact of the \(i^{th}\) position on the \(j^{th}\) position. We call it relation matrix, which measures the similarity between every two pixels in video features. More similar feature representations between the two positions indicates more correlation between them. Therefore, the non-local operation can apply the attention to all pixels in feature map, which is suitable to fuse adjacent frames and ignore the redundant frames in video clips. Meanwhile, we generate a new feature map \(D \in \mathbb{R}^{C \times H \times W}\) and reshape it to \(\mathbb{R}^{C \times N \times N}\). Then we perform a matrix multiplication between \(M\) and the transpose of \(D\) and reshape the result to \(\mathbb{R}^{C \times H \times W}\).

However, the non-local operation consumes large amount of parameters because of the high dimension of relation matrix \(M \in \mathbb{R}^{N \times N}\), especially for video features. Therefore, we design a new architecture called Separate Non-Local to fuse the information across video frames and across pixels in each frame, which can reach better performance with shallower network. As shown in Figure 3, we design three types of attention modules to explore global contextual information in different dimension. First, we generate two new feature maps \(A_1, A_2, A_3\) and \(B_1, B_2, B_3\) in three branches respectively. Then we reshape them to \(\mathbb{R}^{C \times T \times N_1}, \mathbb{R}^{C \times T \times N_2}, \mathbb{R}^{C \times H \times W \times N_3}\) where \(N_1 = H \times W, N_2 = C, N_3 = T\). And then we perform the matrix production to get three relation matrices \(M_1 \in \mathbb{R}^{H \times W \times H \times W}, M_2 \in \mathbb{R}^{C \times C}, M_3 \in \mathbb{R}^{T \times T}\). \(M_1, M_2\) and \(M_3\) denote the similarity between different spatial contexts, different channels, and different time steps, respectively.

Meanwhile, we feed video feature \(F\) into three convolution layers to generate the new feature map \(D_1, D_2, D_3\). Then we reshape them to \(\mathbb{R}^{C \times T \times N_1}, \mathbb{R}^{C \times T \times H \times W \times N_2}, \mathbb{R}^{C \times H \times W \times N_3}\) respectively. Next, we perform a matrix multiplication between the transpose of \(D_1, D_2, D_3\) and \(M_1, M_2, M_3\) to get the results \(E_1, E_2, E_3\). Finally, we perform an element-wise sum operation between \(E_1, E_2, E_3\) and \(F\). At last, we sum up the features from three branch to get the fusion features.

### 4.3. Channel Attention Residual Block

The channel-wise attention mechanism in residual block (CARB) in the reconstruction module is essential for efficient reconstruction and good performance of VESR. As shown in Figure 2, in CARB, we first perform global av-

\[
M_{ij} = \frac{\exp(A^T \cdot B)}{\sum_{i=1}^{N} \exp(A^T \cdot B)}
\]
Table 1. The configurations of VESR-Net. Conv denotes the convolution layer, CARB denotes the channel-attention residual block. \((X_{1·3},\cdots,X_{i·3},\cdots,X_{t+3})\) denote the input video frames.

Table 2. The quantitative evaluation results on dataset used in the second phase of Youku-VESR Challenge. FLOPs [12] are calculated on low-resolution video frames with the size of 64 × 64.

Table 3. The ablation study on Separate Non-Local (Separate NL) and channel-attention residual block (CARB). FLOPs [12] are calculated on low-resolution video frames with the size of 64 × 64.

5. Experiments and Results

In this section, we introduce the implement details of VESR-Net in Youku-VESR challenge and compare VESR-Net with state-of-the-art algorithms.

5.1. Training Setup

Datasets.  We train and evaluate our method on the dataset used in the second phase of challenge, which contains 1000 video clips. We split 50 videos for evaluation and use the remaining videos for training.

Implementation Details. In our proposed VESR-Net, we adopt five channel attention residual blocks (CARB) as feature encoder to perform feature extraction. We design two VESR-Net with different model sizes: \(VESR-Net_{\text{small}}\) with 20 CARBs and \(VESR-Net\) with 40 CARBs in the reconstruction module, respectively. The channel size in each residual block is set to 128. In all our experiments, we focus on \(4 \times 4\) super-resolution factor. We use video frame patches of size \(64 \times 64\) as inputs and \(256 \times 256\) as outputs in training phase but use the original frame size while testing. The model takes 7 consecutive frames as inputs to reconstruct the middle frame. We implement VESR-Net on PyTorch and train the model with 4 NVIDIA Titan 1080Ti GPUs, each with batch size of 32. We use Adam optimizer [8] with \(\beta_1=0.9\) and \(\beta_2=0.999\). The initial learning rate is set to \(1 \times 10^{-4}\) and the weight decay parameter is 0.8 for each 20 epochs. Since EDVR [19] is the state-of-the-art algorithms in VESR, we compare our method with EDVR on the dataset used in Youku-VESR challenge. We reproduce EDVR following the settings in the original paper and released code [19]. For fair comparison, \(EDVR_{\text{small}}\) adopts 20 residual block, which has the comparable amount of parameters with \(VESR-Net_{\text{small}}\).

5.2. Evaluation Results

As shown in Table 2, our baseline is \(EDVR_{\text{small}}\). After increasing the number of CARB block to 49, EDVR achieves 0.28 dB gain in terms of PSNR compared with \(EDVR_{\text{small}}\). The FLOPs and parameters of EDVR are remarkably larger than \(VESR-Net_{\text{small}}\), but \(VESR-Net_{\text{small}}\) can outperform EDVR with less computation complexity. With the help of our designed Separate NL and CARB, VESR-Net is 0.22dB better than EDVR, which demonstrates the efficiency of VESR-Net.

To evaluate the effectiveness of Separate Non-Local (Separate NL) operation and channel attention residual block (CARB) respectively, we conduct ablation studies on \(VESR-Net_{\text{small}}\) and also compare with \(EDVR_{\text{small}}\) on
Figure 4. The qualitative results of EDVR and VESR-Net on Youku-VESR challenge dataset, where “LR” and “HR” represent the low-resolution and high-resolution frames respectively.

the dataset used in the second phase of Youku-VESR challenge. As shown in Table 3, compared to EDVR_{small}, Model 1 introduces the Separate NL based on EDVR_{small}, achieving an improvement of 0.28dB without increasing much parameters and FLOPs. With our CARB, Model 2 is nearly 0.23dB better than EDVR_{small} with roughly the same model parameters and computational cost, demonstrating the effectiveness of CARB. At last, VESR-Net_{small} introduces both Separate NL and CARB and achieves 0.41 dB, 0.13 dB and 0.18 dB performance gain compared to EDVR_{small}, Model 1 and Model 2 respectively.

We further show some qualitative results of EDVR and
VESR-Net on the dataset used in Youku-VESR challenge. As shown in Figure 4, VESR-Net can clearly restore the detail of subtitle in video frames.

5.3. The Leaderboard Results for Youku-VESR Challenge

Among 1500 registered teams in challenge, 10 teams entered in the final phase and submitted results, codes/executables, and factsheets. We list the score of top 3 teams in Table 4. The score is computed with the following formula: $\text{PSNR score} \times 80\% + \text{VMAF score} \times 20\%$. Our team “Avengers Assemble” ranked the first place in the challenge, with about 0.2 point higher than the second and third teams.

| Team          | Score |
|---------------|-------|
| Avengers Assemble | 37.851 |
| NJU_L1        | 37.681 |
| ALONG_NTES    | 37.632 |

Table 4. The leaderboard results of Youku-VESR challenge, where “Avengers Assemble” is our team while “NJU_L1” and “ALONG_NTES” are the teams ranking in the second and third place.

6. Conclusion

In this paper, we proposed VESR-Net, an efficient network for video enhancement and super resolution. VESR-Net consists of a fusion module that leverages Separate Non-Local to capture the relation among video frames for frames fusion, and a reconstruction module that leverages CARB for efficient frame reconstruction. In Youku-VESR challenge, our proposed VESR-Net beat other competitive participants and ranked the first place.

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