NNVISR: Bring Neural Network Video Interpolation and Super Resolution into Video Processing Framework

Yuan Tong Mengshun Hu Zheng Wang*

National Engineering Research Center for Multimedia Software, Hubei Key Laboratory of Multimedia and Network Communication Engineering, School of Computer Science, Wuhan University, China

ABSTRACT

We present NNVISR - an open-source filter plugin for the VapourSynth¹ video processing framework, which facilitates the application of neural networks for various kinds of video enhancing tasks, including denoising, super resolution, interpolation, and spatio-temporal super-resolution. NNVISR fills the gap between video enhancement neural networks and video processing pipelines, by accepting any network that enhances a group of frames, and handling all other network agnostic details during video processing. NNVISR is publicly released at https://github.com/tongyuantongyu/vs-NNVISR.

CCS CONCEPTS

• Human-centered computing → Visualization; • Hardware → Displays and imagers; • Computing methodologies → Computer vision.

KEYWORDS

open source, video super-resolution, video interpolation, spatiotemporal super-resolution

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1 INTRODUCTION

In recent years, deep learning has brought tremendous advancements in fundamental computer vision tasks, such as image classification [12, 17, 24], object detection [4, 21, 22] and image super resolution [9, 18, 28]. These advancements also shed light to video enhancing tasks, such as super resolution [3, 5, 25–27], interpolation [1, 2, 7, 15, 16, 33], and spatio-temporal super resolution [10, 11, 13, 14, 30, 31, 34].

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However, different from the fundamental tasks which deal with single images, video enhancing tasks deal with videos, which are indefinitely long sequences of images (which is usually called frame), and can be extraordinarily large when in uncompressed form. Such intrinsic characteristics of videos decided that it is unfeasible to process videos like images which load the whole input into computational memory. In fact, uncompressed videos are so large that they can quickly fill up even storage devices, let along memory. To solve this problem, many video enhancement methods [1, 3, 7, 11, 13, 14, 25, 27, 30, 31, 34] actually works on a definite and relatively small number of consecutive frames, thus limiting the amount of data to be processed at a time, while still being able to explore the extra temporal relation in video.

Such change to the task allowed applying deep learning method to video enhancing tasks, but also left the ultimate task of enhancing videos in an half-done state, compared to image tasks where task and network inputs and outputs are aligned and can be directly integrated into current applications. Most video enhancement network implementations expect input to be a tuple of images, so to utilize them one have to first convert video to image file sequence and separate them into tuples, then run the network inference, and finally merge output tuples into sequence and convert to video, which is both inefficient and resource-consuming. Some network implementations do try to support process video by using Python libraries like OpenCV, but is barely usable and far from the requirement of serious video processing, let along performance. Moreover, by processing frame tuples instead of the whole video, video enhancement networks avoided a non-trivial problem of detecting scene changes, across which exploring temporal relation usually brings more noise than information and should generally be avoided.

In developing a practical spatio-temporal video super resolution tool based on our previous work CycMuNet [13] and YOGO [14], we found that most of the work is not specific to our network, and even not specific to the spatio-temporal video super resolution task. Instead, any video enhancement network that produces output frames based on a consecutive tuple of input frames can fit into our design. This motivated us to develop NNVISR, an opensource tool, brings all kinds of video enhancement networks into the video processing framework.

NNVISR is publicly released at https://github.com/tongyuantongyu/vs-NNVISR under the 3-Clause BSD License. The repository contains all the source code and detailed documentation including installation, compilation and network intergration guide. NNVISR also provides binary release on Anaconda, which can be easily installed along with all necessary dependencies using the conda package

^{*}Corresponding author

¹https://github.com/vapoursynth/vapoursynth

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manager. NNVISR is designed as a filter plugin for the open source VapourSynth video processing framework. VapourSynth uses Python grammar to declare processing pipeline, and has mature support for loading video, traditional video processing and piping output to video encoders like FFmpeg and x264. NNVISR uses NVIDIA's TensorRT² framework to provide high performance inference of deep learning network. Therefore, NNVISR is suitable for both quick demo and large-scale deployment. To the best of our knowledge, NNVISR is the first video processing tool to support inter-frame video enhancement using arbitrary neural network.

2 **RELATED WORK**

2.1 **Video Super Resolution**

Video Super Resolution aims to convert video frames into higher resolution by predicting high frequency detail. Compared to image super resolution, video super resolution can utilize temporal information between frames to get better result, but also faces an extra challenge to aggregating information among misaligned frames. Early methods [3, 25] use optical flow to guide spatial warping of frames. TDAN [26] adopts deformable convolution (DCN) [8, 35] to align features between frames, and EDVR [27] further designed a DCN pyramid to perform multi-scale feature alignment. BasicVSR++ [6] combined optical flow and DCN to generate high quality DCN offsets for feature alignment.

Video Interpolation 2.2

Video Interpolation aims to generate non-existent pixels temporary between known pixels, in contrast to Video Super Resolution which generates pixels spatially between known pixels, so every output pixel need to be warped from input frames. Early methods [19, 20] tried to use an adaptive kernel to perform warping, but is very inefficient in term of inference speed. Many flow-based methods [16, 34] use optical flow to guide warping, but the inaccuracy of predicted optical flow usually causes distortion to the result, so extra measures [1, 2] are usually taken to refine the warped frame. There are also methods that generate intermediate frames directly, like CAIN [7] using channel attention and RIFE [15] using distillation to get good result one simple architecture.

2.3 **Spatio-Temporal Video Super Resolution**

Based on the similar nature of video super resolution and video interpolation, Spatio-Temporal Video Super Resolution tries to perform spatial and temporal (interpolation) super resolution in one network to reach both better result and better efficiency. STARnet [11] and CycMuNet [13] jointly learns both spatial and temporal SR task using a mutual learning strategy. Zooming Slow-Mo [30] proposed deformable ConvLSTM to explore global temporal contexts. TMNet [31] further proposed a local temporal feature comparison module to extract short-term motion cues. YOGO [14] further compact ST-VSR by only perform alignment once on all input frames to reach better efficiency.

2.4 Open Source Neural Network Video **Enhancement Tool**

Several open-source tools have been developed to perform video enhancement tasks that are able to read and write video files. MMagic³ implemented video enhancement support using various video superresolution and video interpolation models. Practical-RIFE⁴ implemented video interpolation using RIFE [15]. GMFSS Fortuna⁵ implemented video interpolation based on GMFlow [32]. But these tools simply use OpenCV with its default settings, so they are only suitable for simple demo purposes. Anime4K⁶ implemented simple CNN-based video super resolution and denoising networks using a shader to achieve real-time enhancement during playback, but this approach is not suitable for video processing, and doesn't scale well for more complicated networks.

Under such conditions, VapourSynth gained much attention thanks to its ability to write video process scripts using Python, and many VapourSynth scripts and plugins are developed to perform video enhancement using neural networks. VapourSynth-Waifu2x-caffe7 plugin integrated the Caffe implementation⁸ of the famous waifu2x⁹ image super resolution tool. VSGAN¹⁰, vsrife¹¹ and vs-gmfss fortuna¹² each implemented VapourSynth processing script using the Py-Torch implementation of image super resolution model ESRGAN [29], video interpolation model RIFE [15] and video interpolation tool GMFSS_Fortuna, and supports TensorRT speed up using Torch-TensorRT¹³. vs-mlrt¹⁴ plugin further integrates multiple neural network inference engines into VapourSynth, with support for arbitrary image enhancement models and RIFE interpolation model. VSGAN-tensorrt-docker¹⁵ implemented VapourSynth processing script for various video enhancement network, and packed into a docker image for easy use.

3 DESIGN

NNVISR provides simple interface for both end user to processing video, and implementors to provide their network definition. On top of that, NNVISR also integrates well into current VapourSynth ecosystem, and can cooperate with other plugins to build an advanced processing pipeline.

3.1 Network Integration

NNVISR designed a simple yet expressive interface for neural network model to implement, in order to be utilized during video processing.

NNVISR focus on supporting the kind of video enhancement neural networks that explores temporal relationship between a definite number of consecutive frames that we call as frame group.

⁷https://github.com/HomeOfVapourSynthEvolution/VapourSynth-Waifu2x-caffe

²https://developer.nvidia.com/tensorrt

³https://github.com/open-mmlab/mmagic

⁴https://github.com/hzwer/Practical-RIFE

⁵https://github.com/98mxr/GMFSS Fortuna

⁶https://github.com/bloc97/Anime4K

⁸https://github.com/lltcggie/waifu2x-caffe

⁹https://github.com/nagadomi/waifu2x

¹⁰https://github.com/rlaphoenix/VSGAN 11 https://github.com/HolyWu/vs-rife

¹²https://github.com/HolyWu/vs-gmfss_fortuna

¹³ https://github.com/pytorch/TensorRT 14https://github.com/AmusementClub/vs-mlrt

¹⁵https://github.com/styler00dollar/VSGAN-tensorrt-docker

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We separate the whole process into two stages: the extract stage and the fusion stage. The extract stage operates on single frame and produces a pyramid of features in different spatial dimensions (Networks that do not use feature pyramid can be treated as a pyramid of only one layer). The fusion stage mixes the features of all frames in a frame group to produce output frames.

For convenience, we define n to be the number of frames being "consumed" by the network for each inference run. Note that for interpolation networks, the last frame of a frame group is usually also the first frame of the next frame group, so in this case n is the number of input frames minus 1. Based on this definition, we introduced several flags to precisely describe network behavior:

- "Interpolation" flag means the network is doing video interpolation, and instruct NNVISR to produce output video in doubled framerate.
- "Extra frame" flag means the network accepts n + 1 frames rather than n.
- "Double frame" flag means the network produces 2*n* frames for each inference run, otherwise *n*. If "Double frame" flag is not set and "Interpolation" flag is set, then input frames are also used as output frames as is, and network outputs are all treated as intermediate frames.

To integrate neural network into NNVISR, researcher should provide their network definition in ONNX¹⁶ format, which is widely supported by deep learning frameworks. Notably, PyTorch has builtin support for automatically exporting model into ONNX format. Specially, we recognized broad usage of Deformable Convolution [8], especially the V2 [35] variant, among video enhancement networks, mainly due to it's ability to efficiently adapt to arbitrary object motion using its offset input, which is crucial in aligning object among frames and warping frames based on optical flow information. However, while Deformable Convolution plays an important role in video enhancement networks, it does not have wide support, especially is not natively supported by TensorRT. TensorRT has a plugin interface to support custom network operators, so we implemented the V2 variant of Deformable Convolution for TensorRT. It is also compatible with PyTorch's Deformable Convolution implementation provided in torchvision, so networks trained using PyTorch can be directly used.

NNVISR supports input and output in both RGB and YUV pixel format, and implementors can choose to support either or both. RGB is the most common pixel format used in computer vision, while the YUV420 variant of YUV pixel format is the dominant format for video storage and processing. Output in YUV pixel format has two advantages: one being more efficient since YUV420 halves the spatial dimension of 2 in 3 of its channels, therefore has only half the amount of data compared to RGB; another being higher quality because convential conversion from RGB to YUV420 has been shown to be suboptimal, especially for high dynamic range contents [23]. By training to output frame in YUV420 format neural networks can easily achieve better visual quality compared to conventional conversion method.

NNVISR detects colorspace information in videos and loads the network trained for the corresponding colorspace, since same pixel value can and usually mean different colors under different colorspace. Therefore implementors should train their networks on datasets in different colorspace separately, so that the network can produce better result. Color preciseness is crucial to video processing, especially on high dynamic range contents, which are gradually gaining popularity recently.

3.2 End User Usage

The usage of NNVISR is simple. NNVISR follows the idiomatic design of VapourSynth plugin, which provides a single function that accepts an input video (conventionally called "clip" in VapourSynth) and parameters, and returns the enhanced video.

By setting scale factor and flag parameters to different values, NNVISR can be configured to perform various kinds of video enhancing tasks:

- Setting scale factor to 1 to perform video denoising or .
- Setting scale factor > 1 to perform video super resolution.
- Specially, setting horizontal scale factor to 1 and vertical scale factor to 2 to perform video deinterlacing.
- Setting scale factor to 1 and "Interpolation" flag to perform video interpolation.
- Setting scale factor to 1, "Interpolation" flag and "Double frame" flag to perform video interpolation along with denoising.
- Setting scale factor > 1, "Interpolation" flag and "Double frame" flag to perform spatial-temporal video resolution.

Usually real-world videos contains more than one scene while video enhancement models are only trained on a single scene. Therefore when crossing the scene boundary, enhancement result is usually bad so this should be avoid. VapourSynth framework has a standard way to signal the occurence of scene change, therefore user can choose the most suitable plugin to detect scene change based on the video content and user's need. There are already multiple filters that detects scene change using traditional method, and employing a neural network to detect scene change can also be easily implemented.

In addition to source code, we also publish pre-built binaries for Windows and Linux as conda packages, so that users can easily install NNVISR without going through the complicated environment configuations.

3.3 Internal Design

NNVISR internally performs the grouping of frames, taking account of n of network and scene change. For interpolation networks, NNVISR uses a carefully designed frame layout to reduce unnecessary memory usage as much as possible.

NNVISR always grouping frames within a scene, and has a complete set of rules to always output required number of frames. For interpolation network, NNVISR duplicates the last frame of the scene. If the last group doesn't have enough frames for network, last frames from the previous group is recycled to provide enough input frames. If the whole scene does not contain enough input frames then the last frame is further duplicated to satisfy network input count.

Interpolation networks usually require n + 1 input frames, and for a batch of *b*, the naive way need to provide b * (n+1) frames to

¹⁶ https://github.com/onnx/onnx

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	3	1	2	9	7	8	
0	6	4	5	12	10	11	

Figure 1: NNVISR frame store layout where n = 3 and b = 2. Numbers denote the frame index. Actual store order is column first.

the network. However for a batch of *b*, the total number of related frames is actually b*n+1, and b-1 frames are duplicated and taking extra space. The nature of batching requires the same input from different batch placed at contiguous location in memory. Rather than placing the frames in the natural order, NNVISR use an layout shown in Fig. 1. This layout eliminates the need to duplicate frames and can be extended to any *b*. To process the next batch, only the last frame need to be copied to the location of the second last frame (6 to 5 in the figure).

4 CONCLUSIONS

We have publicly released NNVISR, a versatile video processing tool that supports arbitrary networks and various kinds of video enhancing tasks. Moreover, it's high performance, well documented, easy to use and integrates well into current video processing toolchain. In this report, we introduced the design of NNVISR, as well as the considerations behind. We hope NNVISR can help the adoption of video enhancement research echievements into downstream industrial applications.

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