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SURVEY ON VIDEO SUPER RESOLUTION WITH QUALITY ENHANCEMENT

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Abstract

Now Streaming work is going very popular with video super resolution (VSR). There is no good way to access quality video from the low upscaled frames. To solve this we are using VSR. Reconstruct low to high quality video. VSR methods have done a great progress in hands with deep learning, neural network, compression, image restoration, degradation and Upscalers with different method for the better Quality Enhancement of video. They study shows different methods used in VSR Quality Enhancement. We discussed few important architecture, implementation and benchmark dataset used in VSR. We review different architecture and techniques and the result of LPIPS, PSNR, SSIM and VMAF.

Introduction.

Super resolution (SR) methods can increase low quality frames with multiple images, SR images for further improved video quality and create new possibilities for further content analysis. The images and single images and multiple images are in the form of Low Resolution(LR). SR mainly focused primarily on increasing the quality of the resulting image despite potentially losing context accuracy to HR. Methods may produce an overcome incorrect digit, character, face, or other structural object even though they otherwise yield good visual quality. The reconstruction of image is very needful for get proper output VSR. VSR can be used in several applications such as online games, live sports, medical emergence, online classes and other live video streaming to enhance the Quality output.

Video super-resolution (VSR), which gathers data from multiple closely related but misaligned frames in video sequences, presents an additional challenge compared to single-image super-resolution, which concentrates on the intrinsic properties of a single image for the upscaling task.

In order to find a more general, effective, and simple-to-implement baseline for VSR, it is necessary to step back and reevaluate the various designs of VSR models. We begin our search by segmenting popular VSR approaches into submodules based on functionalities. The majority of current methods include four interconnected components: propagation, alignment, aggregation, and upsampling.

Blur

Blur is a typical form of image degradation. The blur in the model comes from both the HR and LR space (Hoogeboom, Emiel 2022). A different SISR degradation model that is frequently used. The HR image has been convolutionally blurred using a blur kernel. This HR blur prevents aliasing and shields more spatial information from downsampling. For the SISR task, the Gaussian kernels blur the LR image primarily using isotropic Gaussian kernels and Baniso with anisotropic Gaussian kernels Limballe, Annabelle,2022). linear blur filter (kernel). Gaussian filters that are anisotropic and isotropic are also frequently used.

Gaussian blur kernel k with a kernel size of 2t + 1, its $(i, j) \in [-t, t]$ element is sampled from a Gaussian distribution normally . Blur kernels could produce sharper outputs for several real samples

$k(i, j) = 1/N \exp(-1/2\, C^T \Sigma^{-1} C), \; C = [i, j]^T$ (1)

Downsampling

The spatial resolution is decreased while the two-dimensionalness is maintained (2D). We also use the Ds bilinear and Ds bicubic downsampling methods, which stand for bicubic and bilinear downsampling, respectively. In addition, a down-up-sampling technique called Ds down-up(= D s/a downDaup) downsamples an image with a scale factor before upscales it. blur brought on by upscaling in both the LR and HR images.

Resize (Downsampling).

create low-resolution images in SR. Think about downsampling and upsampling. to modify an operation. having a variety of resizing algorithms, including nearest-neighbor interpolation, area resizing, bilinear interpolation, and bicubic interpolation. Different resize operations have different effects; some yield blurry results, while others might produce overly sharp images with overshoot artifacts. We consider a random resize operation from the aforementioned options in order to include more varied and complex resize effects. We do not consider nearest-neighbor interpolation and instead focus on the area, bilinear, and bicubic operations. This is because nearest-neighbor interpolation introduces the misalignment problem.

Noise.

There are two types of typical noise: additive Gaussian noise and Poisson noise. (Mannam, Varun, et al, 2022) The probability density function of addictive Gaussian noise is the same as that of the Gaussian distribution. The Gaussian distribution's standard deviation, or sigma value, determines how loud the data will be. Color noise is created when independent sampled noise is present in each RGB image channel(Kong, Linghai, et.al,2022).. The Poisson distribution is followed by Poisson noise. It is typically applied to roughly model the statistical quantum fluctuations-induced sensor noise. intensity inversely proportional to that of the image, and the noises at various pixels are unrelated.

JPEG compression.

Lossy compression is the most popular technique for digital image compression. channel-based downsampling that converts images into the YCbCr colour space. Following the division of images into 8 * 8 blocks and 8 * 16, a two-dimensional discrete cosine transform (DCT), followed by a quantization of DCT coefficients, is applied to each block. More information about JPEG compression algorithms.(Li, Peiya, et al, 2022)(Rahmati, Mohammad 2022)

Scale

Super-Resolution Convolutional Neural Network (SRCNN) is trained to work with just one scale factor for the scale that is selected. A new scale is needed, and a new model needs to be trained. Individual machines are ineffective and unusable for dealing with multiple scales in all conceivable situations. In this study, we design and train a single network to handle SR problems of various scales. Actually, this is very effective. When compared to a single-scale expert, our single machine performs admirably for the designated sub-task. For three scale factors, the number of parameters can be reduced by three times. Although SRCNN uses a variety of learning rates for different layers to achieve stable convergence (Jain, Purab Alok, and Pranali K. Kosamkar, 2022)(Mohan, Amrita,2022).

Grid Connections.

The vision tasks and object detection using grid-like designs. There are two types: frame interpolation and semantic segmentation. Grids are used across resolutions to capture both fine and coarse information during the decomposition of a given image at various resolutions. The use of multiple scales is possible. grid configuration for bidirectional propagation across time. to repeatedly fine-tune the features, enhancing expressiveness, by connecting various frames with a grid.

Higher-Order Propagation.

The various tasks that include HOR include language modelling and classification. Temporal alignment, which has been shown to be crucial to the VSR task, is not taken into account by these methods. The offset diversity provides the temporal alignment in the Deformable Alignment flow-based second-order propagation alignment. multi-scale pyramid cascading deformable (PCD) alignment. during training, optical flow acts as a loss function. On the other hand, we directly include optical flow as base offsets in our module.

Background

The issue of recovering spatial high-frequency components from video frames with low resolution is known as video super-resolution (VSR). With VSR, you can reconstruct a single frame using additional information from nearby frames and long-range temporal correlations, in contrast to single image super-resolution, where methods are constrained to using image priors. Since this is the case, the primary difficulties in VSR lie in effective frame alignment and fusion of salient features along the temporal axis. The ability to run algorithms online and in real-time, where minimal latency and high processing speed are essential, is crucial for many practical applications, including TV and video streaming. High performance, however, strongly correlates with computational complexity in deep neural networks, and strict time constraints in online video processing present significant challenges for learned VSR.

Single-image Super-resolution

The process of super-resolution involves converting low-resolution images into high-resolution ones. To combine and restore a high-resolution image from multiple images taken simultaneously, use multi-image super-resolution (MISR)(Kowaleczko, Pawel, et al,2022, Sun, Kaicong, et al, 2022). Convolutional neural networks are the foundation of the SRCNN model for single image super resolution. the more efficient super-resolution models for images. The network's deconvolution layer, located at the very end, directly learns how to map low-resolution images to high-resolution ones. A lattice block is used to create a light-weighted model that keeps the same SR performance while cutting in half the number of parameters. The LapSRN model (Lu, Yuqi, et al. 2022), which gradually recovers the sub-band residuals of high-resolution images was created using SR models at various scales.

Image Super-Resolution

The conversion of LR resolution images to HR resolution images. A HR image can be created using the series of images from a scene. Mappings between low-quality and highquality images from large-scale paired datasets. a flurry of CNN-based models have been proposed to improve model. We currently use four different types of single super resolution algorithms: prediction models, edge-based techniques, image statistical techniques, and patch-based techniques (Wang, Peijuan, et al, 2022, Gao, Dandan, and Dengwen Zhou, 2023).

Deep Learning for Image Restoration

Deep learning has boundaries of Artificial Intelligence to unlock potential image processing (Xu, Mingle, et al, 2023, Sharma, Prasen, et al, 2023). Some samples deep learning alorithems for image restoration among several techniques. Convolutional Neural Networks (CNNs), Long Short Term Memory Networks (LSTMs) Recurrent Neural Networks (RNNs) Generative Adversarial Networks (GANs) Radial Basis Function Networks (RBFNs) Multilayer Perceptrons (MLPs) Self Organizing Maps (SOMs) Deep Belief Networks (DBNs) Restricted Boltzmann Machines(RBMs) Autoencoders.

Real-World Super-Resolution

To overcome these challenges of real-world super-resolution, the combined with denoising or deblurring(Chen, Honggang, et al, 2023 Chen, Honggang, et al,2022 Zhang, Jizhou, et al 2022), have been proposed we explicitly estimate the kernel degradation in real images, which is very important for generating clear and sharp results.

Table 1.

Model	LPIPS	SSIM	PSNR	VMAF	Paper
BSRGAN	0.177	0.836	29.27		Designing a Practical Degradation Model for Deep Blind Image Super-Resolution
RealEsrgan	0.181	0.855	29.14		Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data
SwinIR-Real-B	0.183	0.83	28.86		SwinIR: Image Restoration Using Swin Transformer
RealEsrgan-F	0.185	0.85	28.82		Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data
SwinIR-Real-S	0.189	0.845	28.55		SwinIR: Image Restoration Using Swin Transformer
RealBasicVSR	0.201	0.838	29.54		Investigating Tradeoffs in Real-World Video Super-Resolution
RealSR	0.22	0.9	30.64		Real-World Super-Resolution via Kernel Estimation and Noise Injection
RealEsrgan-A	0.244	0.83	28.71		Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data
RealEsrnet-F	0.28	0.868	30.01		Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data

COMISR	0.291	0.871	30.97		COMISR: Compression-Informed Video Super-Resolution
RealEsrnet	0.296	0.878	30.52		Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data
BSRNET	0.301	0.859	30.19		Designing a Practical Degradation Model for Deep Blind Image Super-Resolution
RealEsrgan-V	0.333	0.795	25.52		Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data
BasicVsr++RD	0.334	0.881	30.98		BasicVSR++: Improving Video Super-Resolution with Enhanced Propagation and Alignment
VRT-Reds-L	0.343	0.869	31.01		VRT: A Video Restoration Transformer
SRMD	0.349	0.852	30.96		Learning a Single Convolutional Super-Resolution Network for Multiple Degradations
DynaVSR		0.916	26.12	56.86	DynaVSR: Dynamic Adaptive Blind Video Super-Resolution
VDSR		0.917	25.89	36.46	Accurate Image Super-Resolution Using Very Deep Convolutional Networks
ESPCN		0.926	26.25	47.19	Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network
SRCNN		0.929	26.68	51.21	Image Super-Resolution Using Deep Convolutional Networks
EGVSR		0.929	26.33	60.39	Real-Time Super-Resolution System of 4K-Video Based on Deep Learning
VESPCN		0.932	26.92	53.96	Real-Time Video Super-Resolution with Spatio-Temporal Networks and Motion Compensation
SPMC		0.933	26.99	51.96	Detail-revealing Deep Video Super-resolution
DRRN		0.933	26.97	55.45	Image Super-Resolution via Deep Recursive Residual Network
TecoGAN		0.933	26.6	61.2	Learning Temporal Coherence via Self-Supervision for GAN-based Video Generation

ESRGAN		0.936	27.29	56.69	ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks
FRVSR		0.936	27.23	57.14	Frame-Recurrent Video Super-Resolution
DBVSR		0.937	27.28	57.39	Deep Blind Video Super-resolution
SOF-VSR		0.937	27.14	56.45	Deep Video Super-Resolution using HR Optical Flow Estimation
iSeeBetter		0.939	27.42	57.91	iSeeBetter: Spatio-Temporal Video Super Resolution using Recurrent-Generative Back-Projection Networks
LGFN		0.939	27.42	57.79	Local-Global Fusion Network for Video Super-Resolution

Video Super-Resolution methods and architecture.

To upscale the video resolution and have some existing VSR methods are trained with pre-defined degradations, second order degradation, alignment, image restoration deep learning.

1.BSRGAN

The Designing a Practical Degradation Model for Deep Blind Image Super-Resolution (BSRGAN) (Zhang, Kai, et al, 2021). The practical degradation model and traditional degradations (Jingyun Liang, et al. 2021, Tomer Michaeli and Michal Irani, 2013, Rani, M., and U. Shanker, 2018) that consists of randomly shuffled blur, down sampling (Rombach, Robin, et al, 2022) and noise degradations. By two convolutions with isotropic and anisotropic Gaussian kernels (París, Guillem, et al,2023). The down sampling is randomly chosen from nearest, bilinear and bicubic interpolations(Zhao, LinTong, et al, 2022) which are targeted for SR. New degradation model can help to significantly improve the practicability of deep super-resolvers, thus providing a powerful alternative solution for real SISR.

2.Real-ESRGAN

Training Real-World Blind Super-Resolution with Pure Synthetic Data (Real - Enhanced Super-Resolution Generative Adversarial Networks, Real-ESRGAN) (Wang, Xintao, et al, 2021). Super-Resolution Generative Adversarial Network (SRGAN) (Singla, Khushboo, et al, 2022). Improve each of them to derive an Enhanced SRGAN (ESRGAN) (Wang, Xintao, et al, 2022). They are still far from addressing general real-world degraded images. They restore low-resolution images with unknown and complex degradations. To more accurately simulate intricate real-world degradations, the high-order degradation modeling process is presented in fig 1. To improve discriminator performance and maintain training dynamics, use the U-Net discriminator with spectral normalization. Its superior visual performance on real datasets has been demonstrated through extensive comparisons.

Fig.1.Data generating and second order degradation (Wang, Xintao, et al, 2021)

3.SwinIR

Image Restoration Using Swin Transformer (SwinIR) (Liang, Jingyun, et al, 2021). Deep feature extraction and high-quality image reconstruction(Guo, Shi, et al,2022). The extraction module is composed of several residual Swin Transformer blocks (RSTB) (Xing, Wenzhu, et al, 2022), which has a residual connection and multiple layers of Swin Transformer. Conduct three different tasks shown in fig 2. image super-resolution (including classical, lightweight and real-world image super-resolution), image denoising (including grayscale and color image denoising) and JPEG compression artifact reduction.

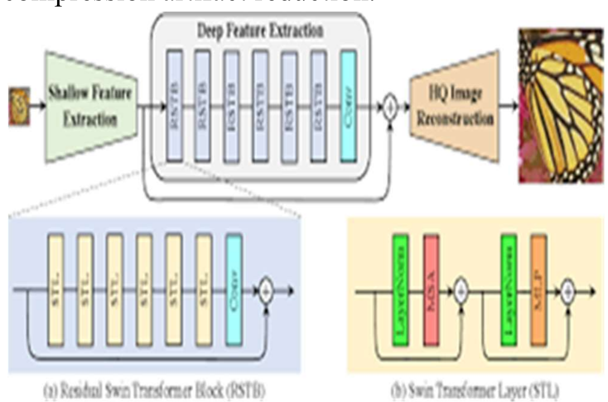

Fig 2: The architecture of the proposed swinIR for image restoration. (Liang, Jingyun, et al,2021)

4.RealBasicVSR

Investigating Tradeoffs in Real-World Video Super-Resolution (RealBasicVSR) (Chan, Kelvin CK, et al. 2022).To validate the performance in cases of mild degradations, Exacerbating severe wild degradations through propagation resulting in output quality.We found that an image precleaning stage was crucial for reducing noise and artifact before propagation in order to strike abalance between the tradeoff between detail synthesis and artifact suppression. Equipped with a carefully designed cleaning module, our RealBasicVSR outperforms existing methods in both quality and efficiency. Increased batch size is necessary to create a stable gradient in order to improve generalizability. The increased computational load inevitably leads to a number of issues, including 1) the speed-performance tradeoff and 2) the batch-length tradeoff.

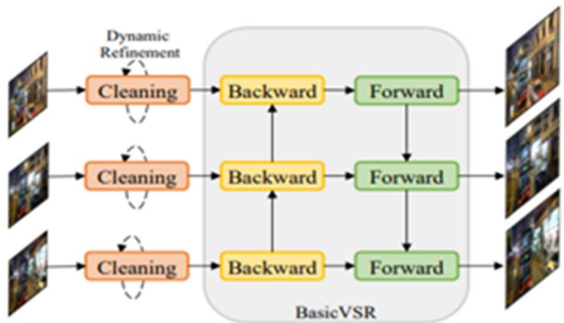

Fig 3. Overview of RealBasicVSR (Chan, Kelvin CK, et al. 2022)

5.RealSR

Real-World Super-Resolution via Kernel Estimation and Noise Injection(RealSR) (Ji, Xiaozhong, et al. 2020). These approaches consistently fall short when it comes to real-world image super-resolution because the majority of them use straightforward bicubic down sampling from high-quality images to create training Low-Resolution (LR) and High Resolution (HR) pairs that might overlook frequency-related details. We concentrate on designing a novel degradation framework for real-world images in order to address this problem by estimating various blur kernels and actual noise distributions fig 4. We can acquire LR images with a common domain with real-world images using our innovative degradation framework.

$I_{LR} = (I_{HR} * k)\downarrow_s + n,$ (2)

Where k and n indicate blurry kernel and noise.

Clean-Up the image and improve sharpness and of the image. we use bicubic downsampling on the original image in the source domain.

$I_{HR}=(I_{src}*k_{bic})\downarrow sc$ (3)

Degradation with Blur Kernels can use downscale for cleaning. The HR images can blur kernel from the degradation pool cross-correlation operations followed by sampling with stride s

$I_D=(I_{HR}*k_i)\downarrow_s, i\in\{1,2\cdots m\}$ (4)

Where as D for downscale K as blur kernel , I as image

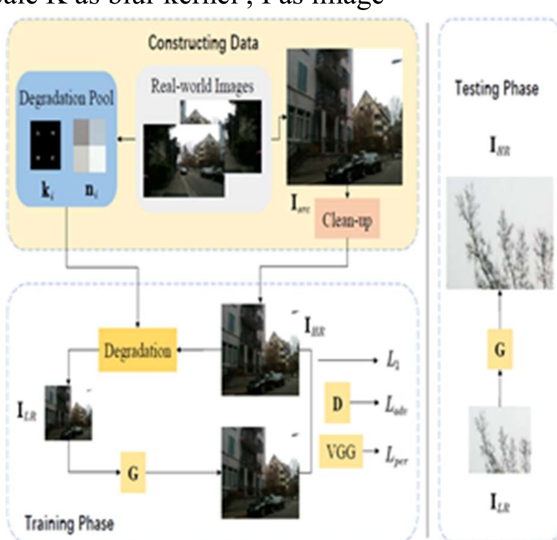

Fig 4. Framework of our proposed RealSR method (Ji, Xiaozhong, et al. 2020)

6.COMISR

Compression-Informed Video Super-Resolution COMISR(Li, Yinxiao, et al, 2021). The Three modules make up the proposed model for video super-resolution: Laplacian enhancement, detail-preserving flow estimation, and bi-directional recurrent warping. These three modules are used to deal with compression properties like where intra-frames are located in the input and how smooth the output frames are.

We conducted extensive tests on standard datasets with a wide range of compression rates, covering many actual video use cases, in order to evaluate performance in-depth. We demonstrated that, in addition to recovering high-resolution content from uncompressed frames of the commonly used benchmark datasets, our method also achieves state-of-the-art performance in super-resolving compressed videos based on a variety of quantitative metrics.

7. BasicVSR++

Improving Video Super-Resolution with Enhanced Propagation and Alignment (BasicVSR++) (Chan, Kelvin CK, et al, 2022) By recommending second-order grid propagation and flow-guided deformable alignment, we redesign BasicVSR. We demonstrate that our model Basic VSR++ outperforms Basic VSR by 0.82 dB in PSNR with a comparable number of parameters by enhancing the recurrent framework with improved propagation and alignment fig 5. Basic VSR++ generalises well to other video restoration tasks like compressed video enhancement in addition to video super resolution.

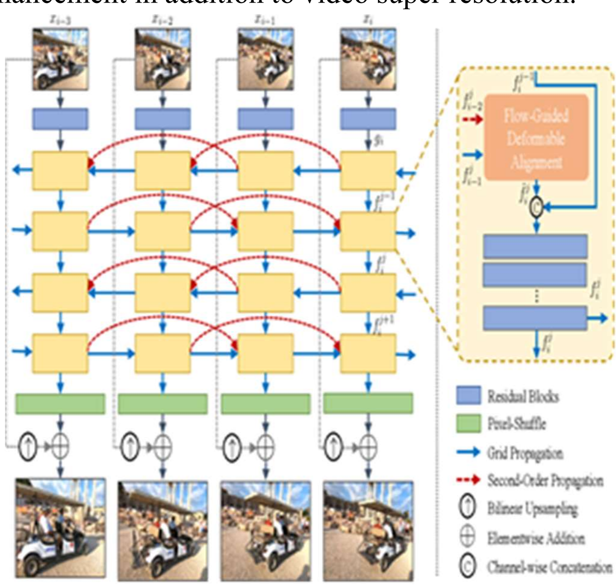

Fig 5. BasicVSR++ (Chan, Kelvin CK, et al, 2022)

8. VRT

A Video Restoration Transformer (VRT)(Liang, Jingyun, et al,2022). Parallel warping and temporal mutual self attention (TMSA) are the two different types of modules that make up each scale in the VRT. In TMSA, the video is divided into short clips. Joint motion estimation, feature alignment, and feature fusion are performed on these short clips using mutual attention, while feature extraction is done using self attention. The video sequence is moved for each additional layer to allow for cross-clip interactions. Parallel feature warping is additionally used to further combine data from nearby frames. Including video super-resolution, deblurring, denoising, frame interpolation, and space-time video super-resolution, which show that VRT out performs the state-of-the-art.

9. SRMD

Learning a Single Convolutional Super-Resolution Network for Multiple Degradations (SRMD) (Zhang, Kai, Wangmeng Zuo, and Lei Zhang, 2018). Single-image super-resolution is used in the proposed study. However, the majority of the current CNN-based SISR methods assume that a high-resolution (HR) image is bicubically down sampled from a low-resolution (LR) image, which inevitably leads to poor performance when the actual degradation does not match this assumption.

10.DynaVSR

Dynamic Adaptive Blind Video Super-Resolution(DynaVSR)(Lee, Suyoung, Myungsub Choi, and Kyoung Mu Lee, 2021). In this paper, they introduced DynaVSR, a novel framework for real-world video SR based on meta-learning, which allows for effective model estimation and input adaptation during downscaling. To be more precise, we train a video SR network for input-aware adaptation in conjunction with a multi-frame downscaling module that uses different kinds of synthetic blur kernels.

Conclusion

We looked at how video quality has evolved for VSR over the years. The generalizability of these designs makes them suitable for other video restoration tasks, such as compressed video enhancement. These parts are general-purpose, and we predict that they will be useful for other video-based enhancement or restoration tasks like deblurring and denoising. While performing admirably on uncompressed videos, the model achieves the most cutting-edge performance on compressed videos in both qualitative and quantitative measures. a new degradation model for deep learning video super-resolution for improving quality.

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