

Quality &  
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Lab



## Quality Enhancement of Gaming Content using Generative Adversarial Networks

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## Image Enhancement Techniques

- Deblocking-oriented
  - E.g. Applying BM3D (block-matching and 3D filtering) [1]
  - Using Wavelets-based [2]
- Deep learning-based (Super Resolution Task)
  - CNN based methods
  - GANs-based methods

[1]. Self-learning-based post-processing for image/video deblocking via sparse representation

[2]. A deblocking algorithm for JPEG compressed images using overcomplete wavelet representations



# Super Resolution Tasks

## CNN based methods

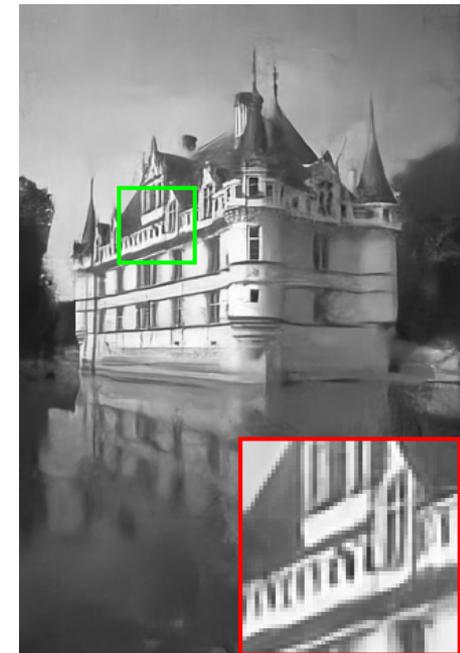
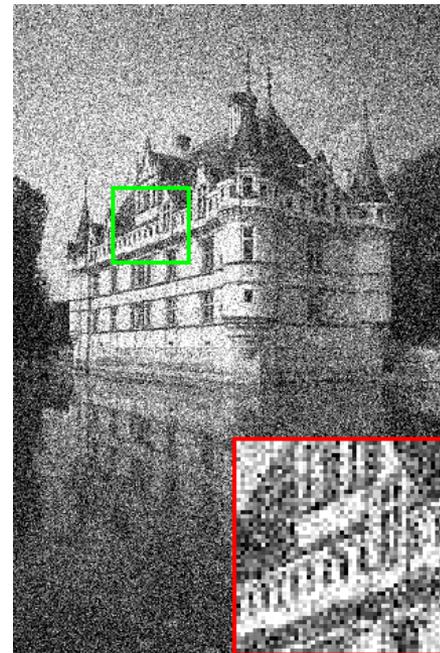
- DnCNNs [1] → for deblocking of Gaussian denoising with unknown noise level and Super resolution task

## GAN based methods

- SRGAN [2] → Capable of inferring photo-realistic natural images for 4× upscaling factors

Before Enhancement

After Enhancement



DnCNNs

[1]. Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising

[2]. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network



# Super Resolution Tasks

**Bicubic**  
(21.59dB/0.6423)



**SRGAN**  
(21.15dB/0.6868)



**Original**



Figure - Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network



# Loss Function

## Pixel-based vs Perceptual-based

- Perceptual quality or reconstruction accuracy?
- FR metric or NR metric for evaluation?



**SRResNet**

(23.53dB/0.7832)

**SRGAN**

(21.15dB/0.6868)

**Original**

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# Gaming Content

## Special Temporal and Spatial Information

- ❑ Game is a **rule-based** system that has special characteristics.
- ❑ A game is usually constructed from a **pool of predesigned objects** which result in different level of details.
- ❑ A game has a **certain level of abstraction**, and that does not vary much during the gameplay.
- ❑ Many games have **specific motion pattern**, e.g. racing game or side scrolling games.



# GAN for Enhancement of Gaming Content

## Research Questions

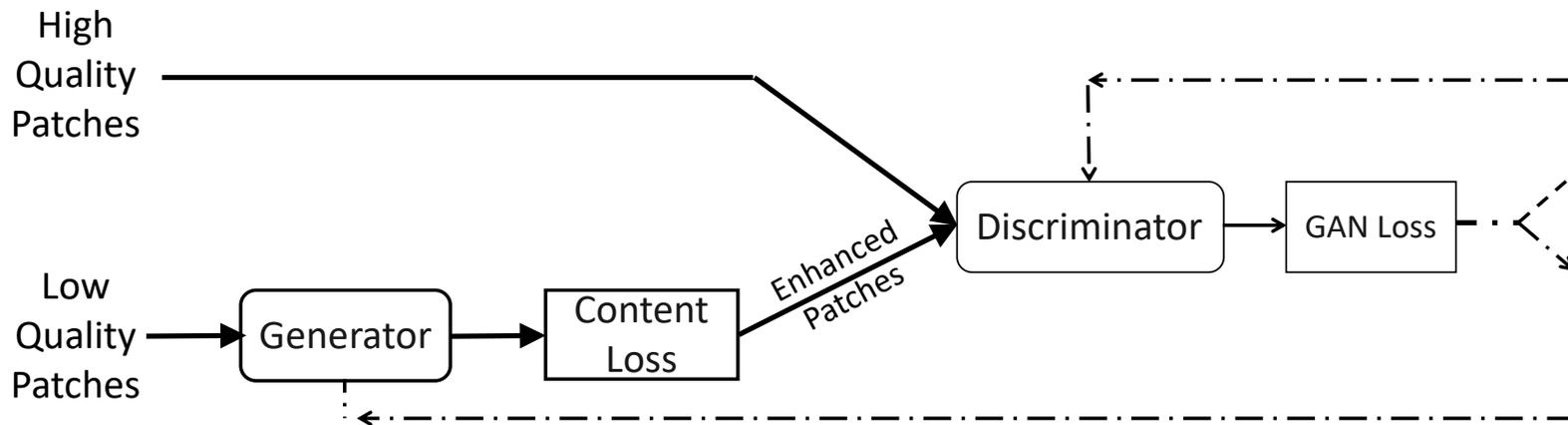
- ❑ Investigate the performance of GANs for quality enhancement of gaming content
  - ❑ **Content Diversity:** Can we have better enhancement for a specific game?
  - ❑ **Enhancement Power:** How much enhancement we may gain?
  - ❑ **Blurriness vs. Blockiness:** Is there any difference in enhancement of different image artifact?



# GAN for Enhancement of Gaming Content

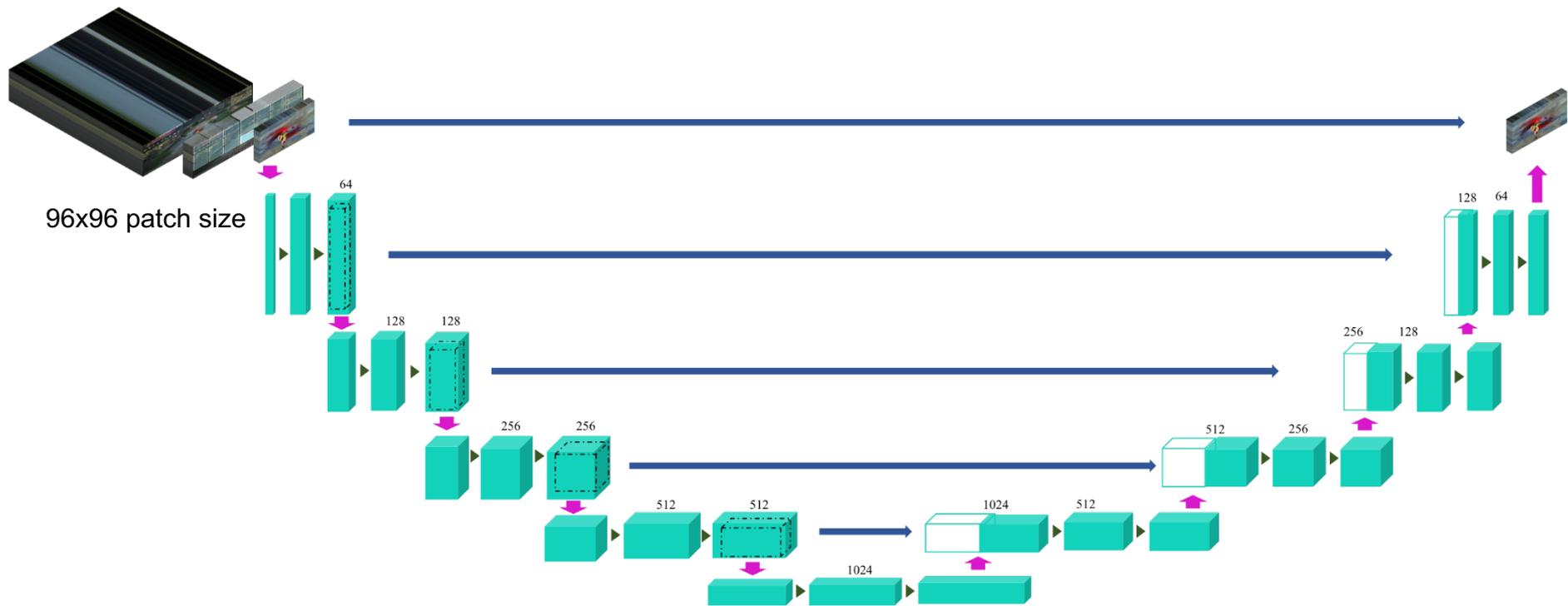
## Updating the model

- ❑ We used SRGAN architecture
  - ❑ Updated the loss function
  - ❑ Used U-NET for generator block
  - ❑ Used deeper CNN for Discriminator





# GAN for Enhancement of Gaming Content Generator





# GAN for Enhancement of Gaming Content

## Loss Function

$$l^{SR} = \underbrace{l_X^{SR}}_{\text{content loss}} + \underbrace{10^{-3} l_{Gen}^{SR}}_{\text{adversarial loss}}$$

perceptual loss (for VGG based content losses)

- ❑ Content Loss: Euclidean distance between the feature representations of a generated image and the reference image
  - ❑ Feature map of the last convolution before max-pooling (VGG19)
- ❑ Adversarial Loss: from discriminator network
- ❑ **Quality Loss**: Pretrained VGG19 for quality task using VMAF.



# GAN for Enhancement of Gaming Content Datasets

- ❑ **Part-1:** The dataset is created based on 100k image patches which are extracted from a single game, League of Legends (LoL).
- ❑ **Part-2:** The dataset is created based on 100k image patches which are extracted from 12 different video games.
- ❑ **Part-3:** The dataset is created based on 100k image patches which are extracted from LoL, but consists of two sub-parts
  - ❑ **Blur:** consisting of patches extracted from 480p and 720p videos up-scaled to 1080p videos using bicubic method.
  - ❑ **Blockiness:** consisting of patches extracted from frames from 1080p videos encoded at various bitrate levels.



# GAN for Enhancement of Gaming Content

## Patch Selection

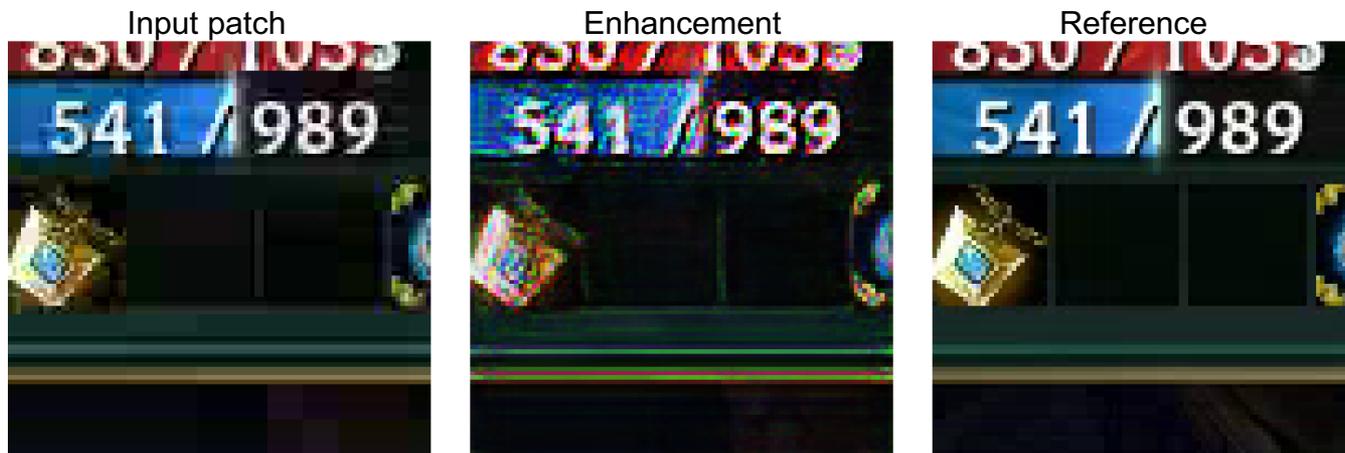




# Results

## Observation

- ❑ Perceptual Quality vs. Image reconstruction
  - ❑ Using pixel-wise metrics in the loss function allows the model to predict the text in the image well
- ❑ Add-up Distortion:
  - ❑ If the quality is already high, we observed additional distortion





# GAN for Enhancement of Gaming Content

## Enhancement Power

### ❑ Dataset Part-1:

- ❑ Class 1 and 2 consisting of frames with Blockiness artifact with VMAF values range between 20 - 40 and 40-60 respectively
- ❑ Class 3 and 4 consisting of frames with Blurriness artifact with VMAF values range between 20 - 40 and 40-60 respectively.

	NIQE		PIQE	
	Distorted	Enhanced	Distorted	Enhanced
Class-1	5.5	2.79	70.67	24.1
Class-2	3.69	2.73	56.1	18.06
Class-3	5.8	2.69	74.8	27.21
Class-4	3.94	2.62	61.36	20.1



# GAN for Enhancement of Gaming Content

## Content Diversity

- ❑ **Comparing Dataset Part-1 and Part-2:**
  - ❑ Class 1 and 2 consisting of frames with Blockiness artifact with VMAF values range between 20 - 40 and 40-60 respectively
  - ❑ Class 3 and 4 consisting of frames with Blurriness artifact with VMAF values range between 20 - 40 and 40-60 respectively.

	NIQE		
	Distorted	Enhanced Part-1	Enhanced Part-2
Class 1	5.5	2.79	3.21
Class 2	3.69	2.73	3.32
Class 3	5.8	2.69	3.11
Class 4	3.94	2.62	3.91



# GAN for Enhancement of Gaming Content

## Blurriness vs. Blockiness

- ❑ **Dataset Part-3:**
  - ❑ Selected 40 pairs of LoL frames with similar quality level in terms of VMAF, one part with blockiness and the other with blurriness artifacts.
  - ❑ Class-1 with VMAF value ranges from 20 to 40.
  - ❑ Class-2 with VMAF value ranges from 40 to 60.

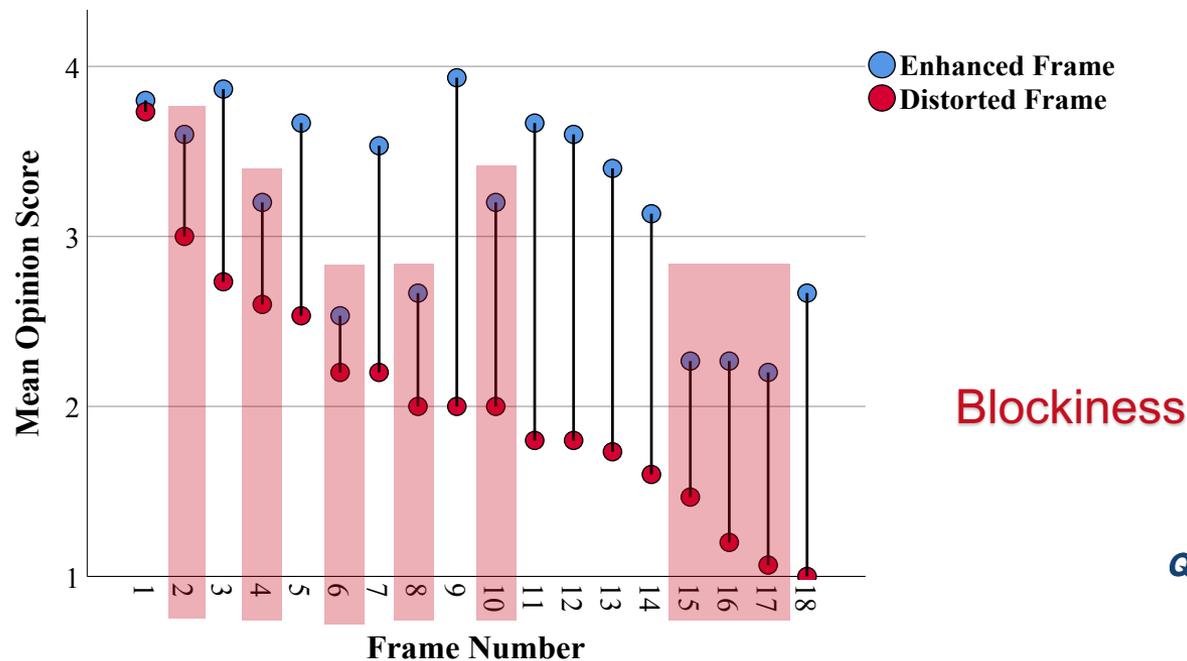
	NIQE Improvement		PIQE Improvement	
	Blurriness	Blockiness	Blurriness	Blockiness
Class-1	2.68	2.21	45.15	37.36
Class-2	1.54	1.14	34.35	28.16



# GAN for Enhancement of Gaming Content

## Subjective Quality Assessment

- ❑ **Dataset Part-3:**
  - ❑ Selected 2 reference frames from the game LoL
  - ❑ 9 distorted frames are selected from each reference frame

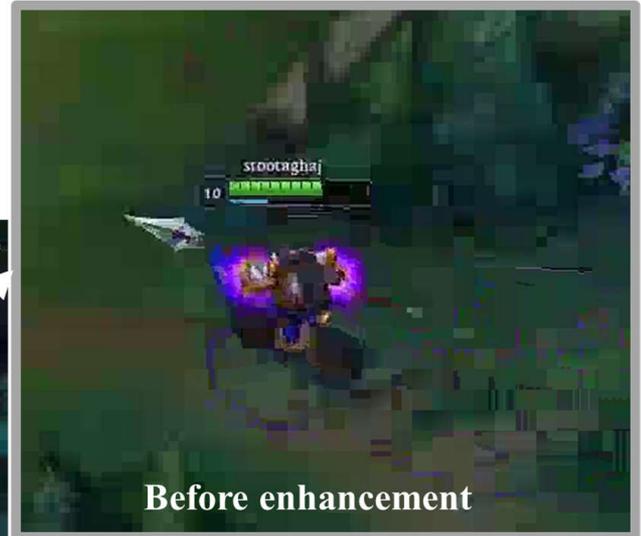




Before enhancement

After enhancement

Single Gaming Video Frame



Before enhancement



After enhancement



## Discussion and Conclusion

- Copy-right issue
- Video quality enhancement
- There is a lot to do on loss function
- Mixture of deblocking and deep learning methods might be a good option for image quality enhancement of blockiness artifact
- Gaming content benefits from similarity of content
- Research on lighter version of deep learning models for enhancement technique



Thank you for your Attention!!  
Any Question?

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