

# RTSR: Enhancing Real-time H.264 Video Streaming using Deep Learning based Video Super Resolution

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# Problem

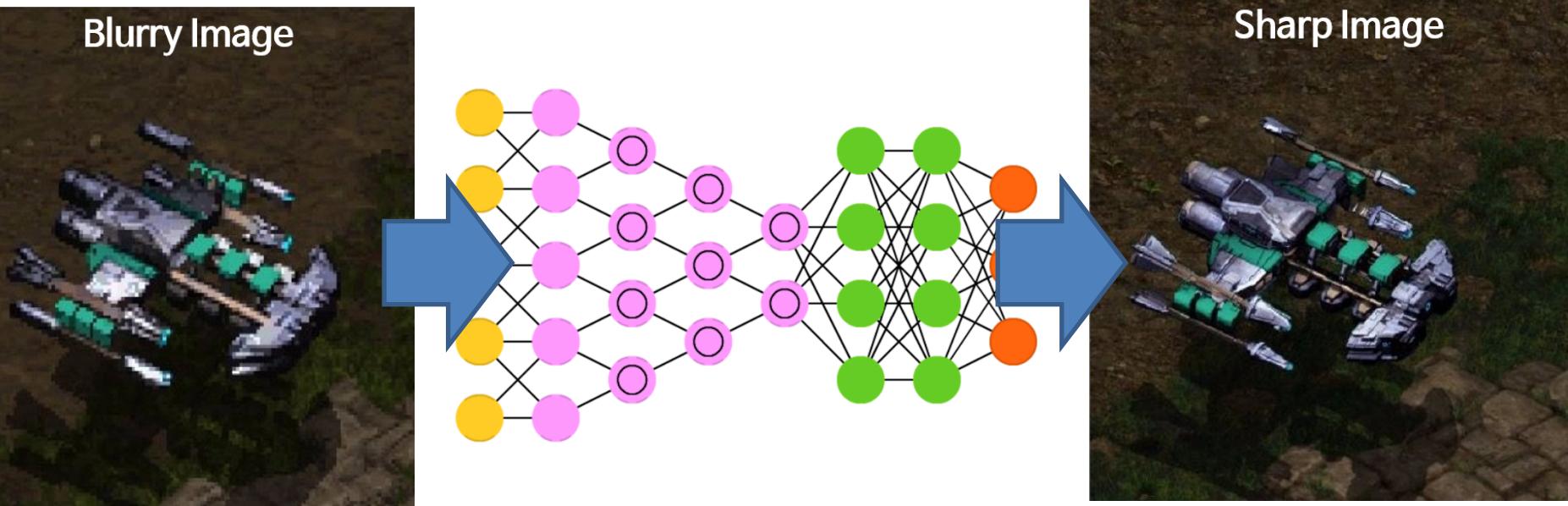
## Streaming Server



**High-quality**  
compression technique causes  
**video quality loss**

# Super-Resolution (SR)

Super-Resolution technique makes image more sharper

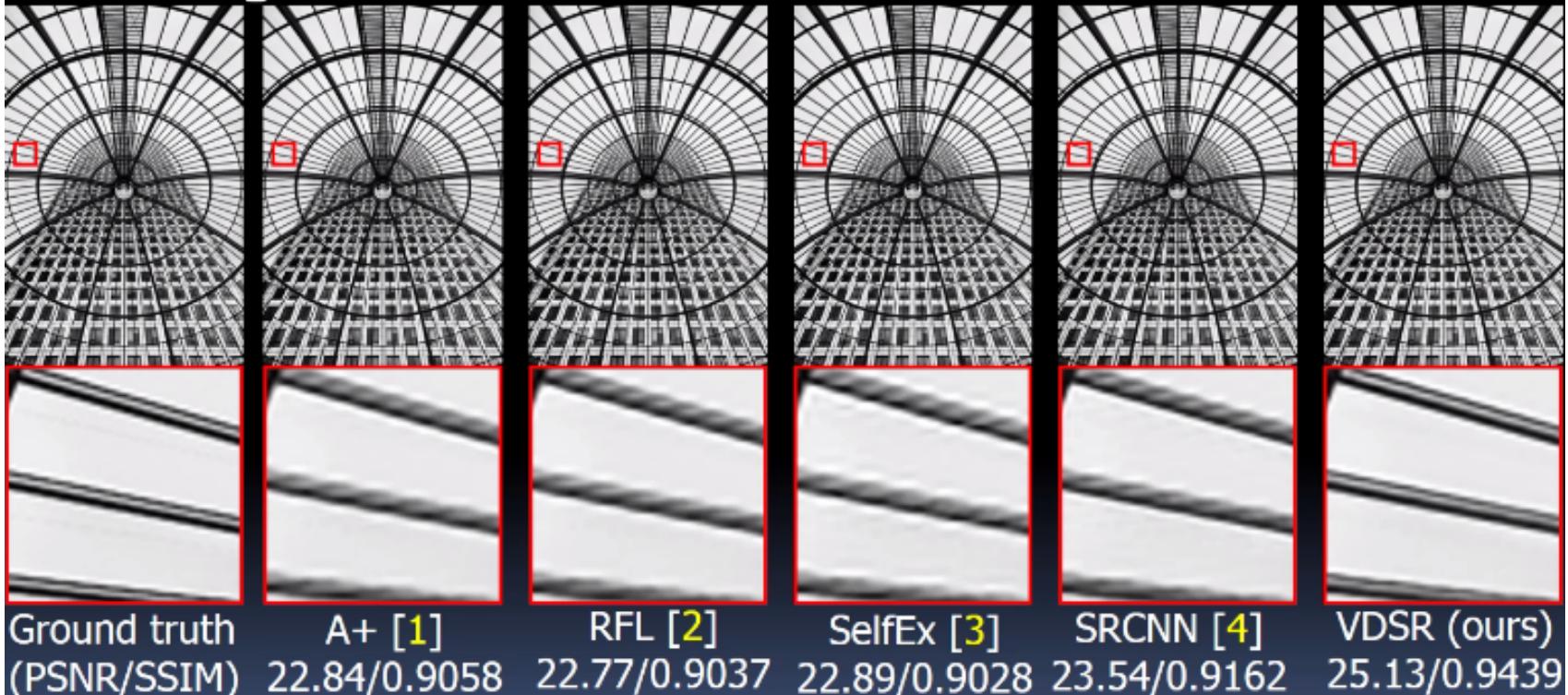


**Super-Resolution**

# Single Image Super-Resolution

Accurate Image Super-Resolution Using Very Deep Convolutional Networks - Kim et al. (CVPR16)

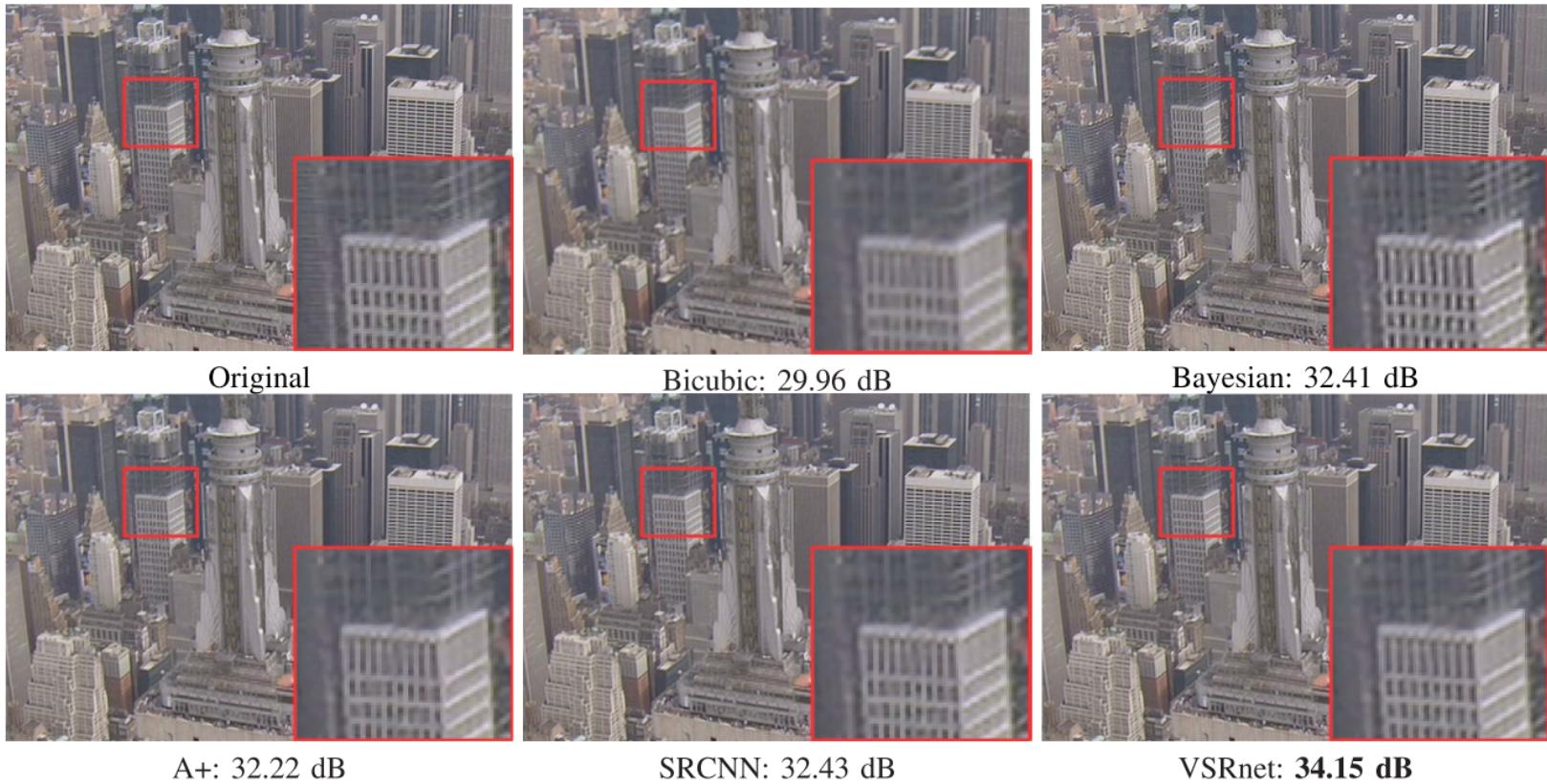
- “img072” of Urban100 for scale factor  $\times 2$



Fast super-resolution technique but it's target is not video<sub>5</sub>

# Video Super-Resolution

Video super-resolution with convolutional neural networks - Kappeler et al. (TCI16)



The processing time is about 10 seconds per frame.  
→ not suitable real-time video processing

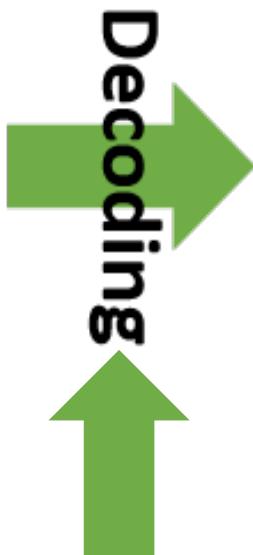
# Goal

F  
C  
C

End-user



Encoded Video



Decoded Video

SR model

Hig  
Orig

overed

# Approach

Exploit data structure used in video compression:  
**Group of Picture (GOP)**

How H.264 codec reduces the size of video?

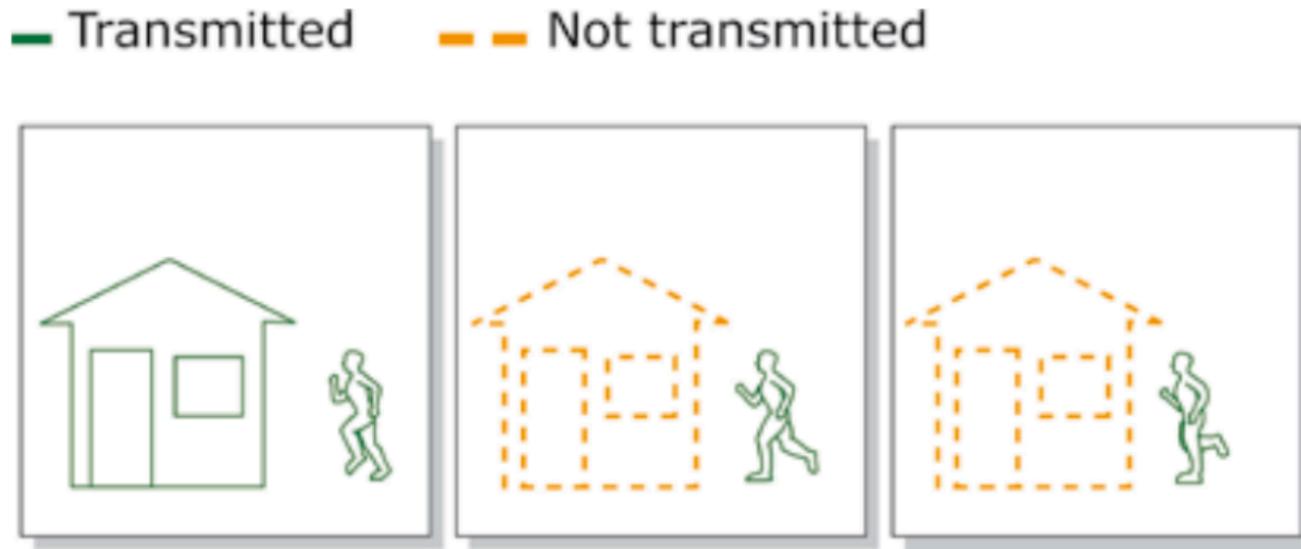


A video containing 3 frames.  
Pixel information for home is duplicated

# Approach

Exploit data structure used in video compression:  
**Group of Picture (GOP)**

How H.264 codec reduces the size of video?



H.264 does not store home in 2<sup>nd</sup> and 3<sup>rd</sup> frame

# Approach

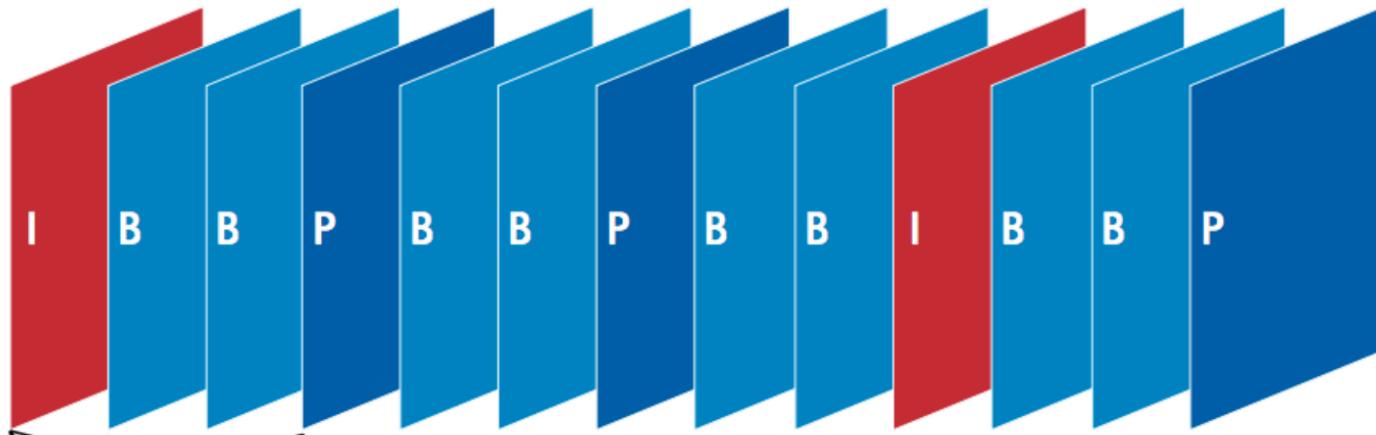
Exploit data structure used in video compression:  
**Group of Picture (GOP)**

How H.264 codec reduces the size of video?



# Approach

Exploit data structure used in video compression:  
Group of Picture (GOP)



GOP: Group of frames (I-, P-, or B-)  
There should be  $1 \geq I$ -frame in GOP

4~8 frames in a GOP is ideal for LTE [1]  
30~60 frames in a GOP in practical [2, 3]

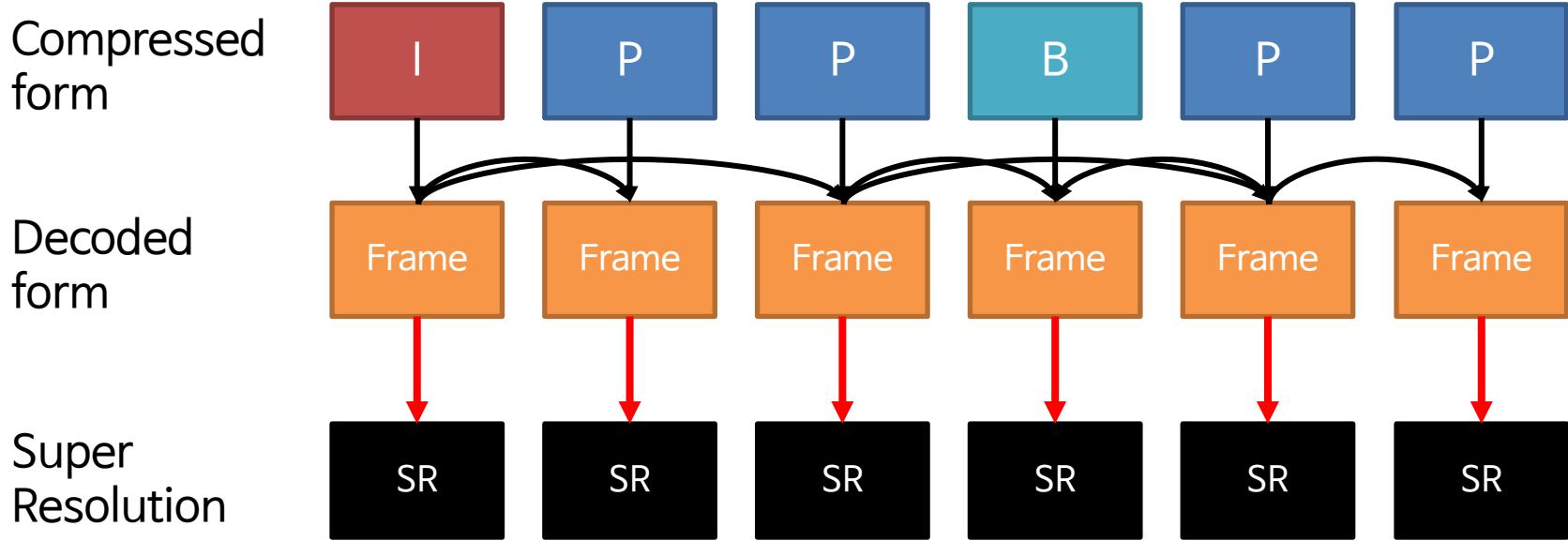
[1] Zulpratita, Ulil S. "GOP length effect analysis on H. 264/AVC video streaming transmission quality over LTE network." (2013).

[2] Twitch TV, Broadcast Requirements. [Online] <https://help.twitch.tv/customer/portal/articles/1253460-broadcast-requirements>

[3] Youtube Help, Live encoder settings, bitrates, and resolutions. [Online] <https://support.google.com/youtube/answer/2853702?hl=en>

# Approach

Performing super resolution on video..



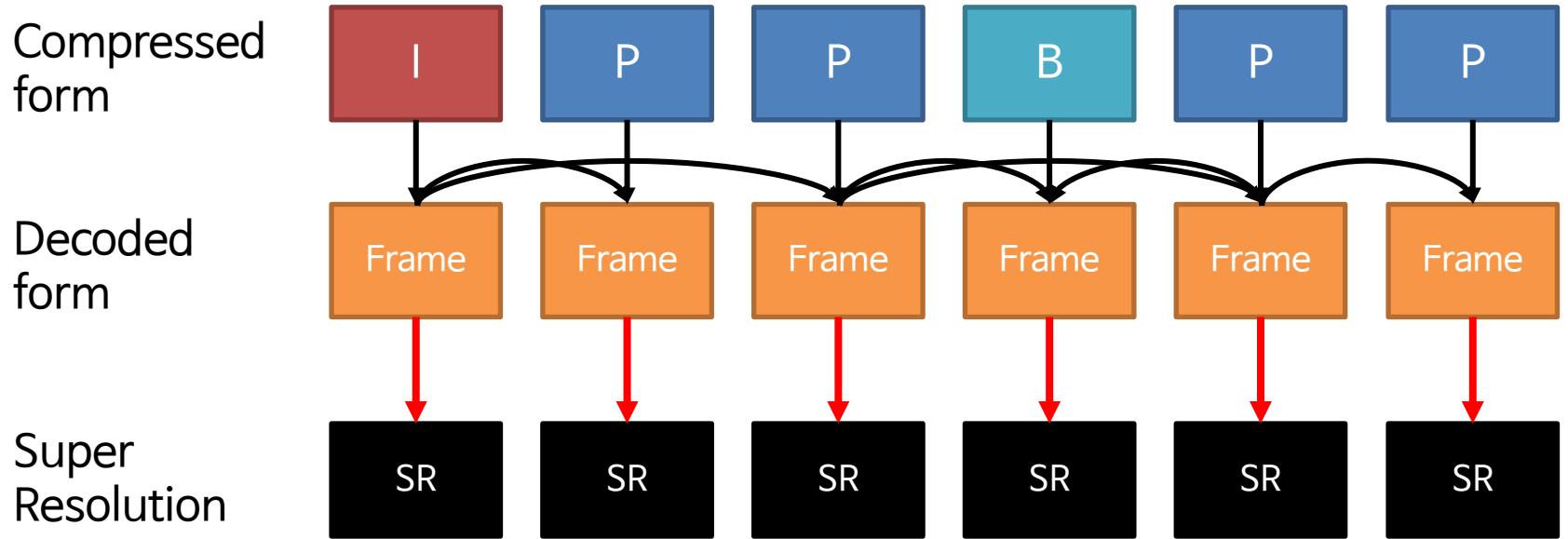
**Performing super resolution for every frame**

SR cannot be done in a frame interval

High computation overhead

# Approach

Performing super resolution on video..



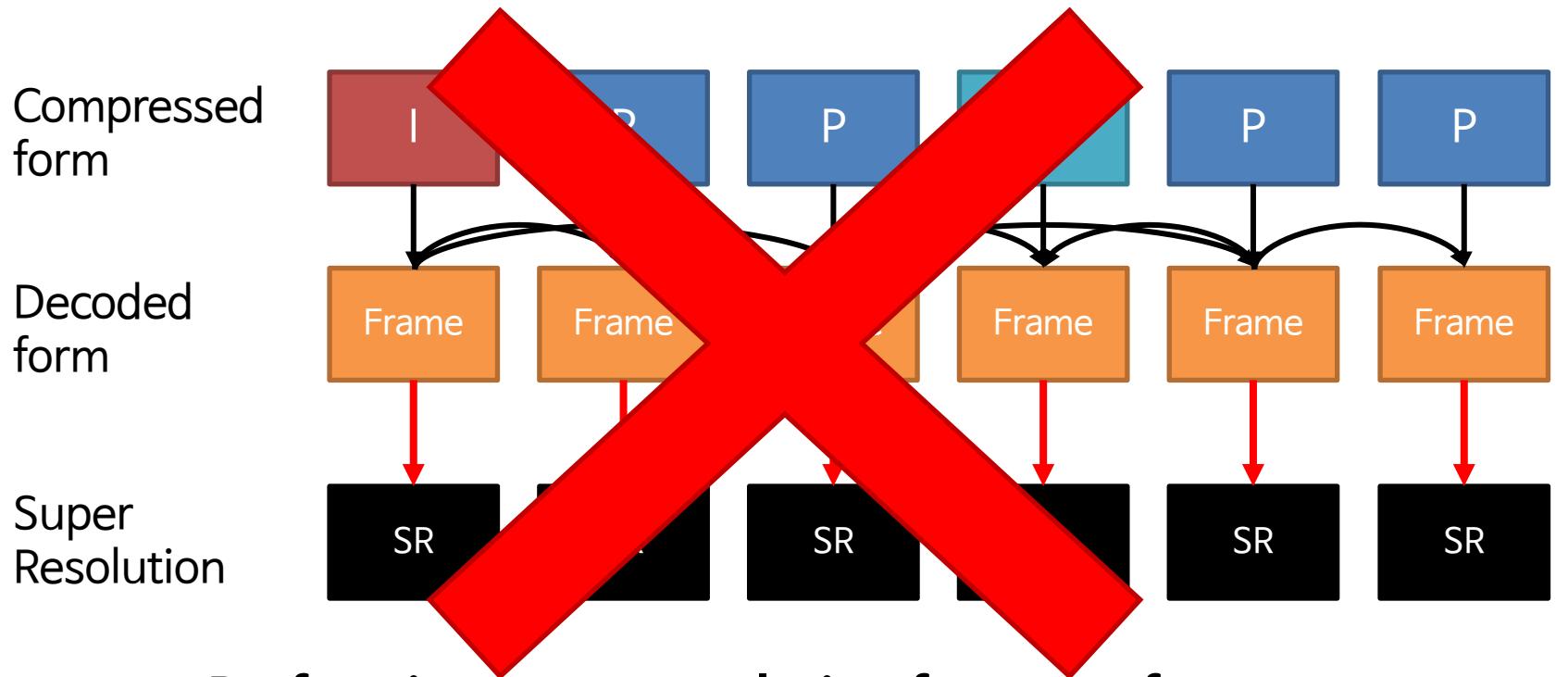
Performing super resolution for every frame

SR cannot be done in a frame interval  
High computation overhead

Frame interval	0.03s
VDSR	0.1s
SRCNN	2s
A+	0.9s

# Approach

Performing super resolution on video..



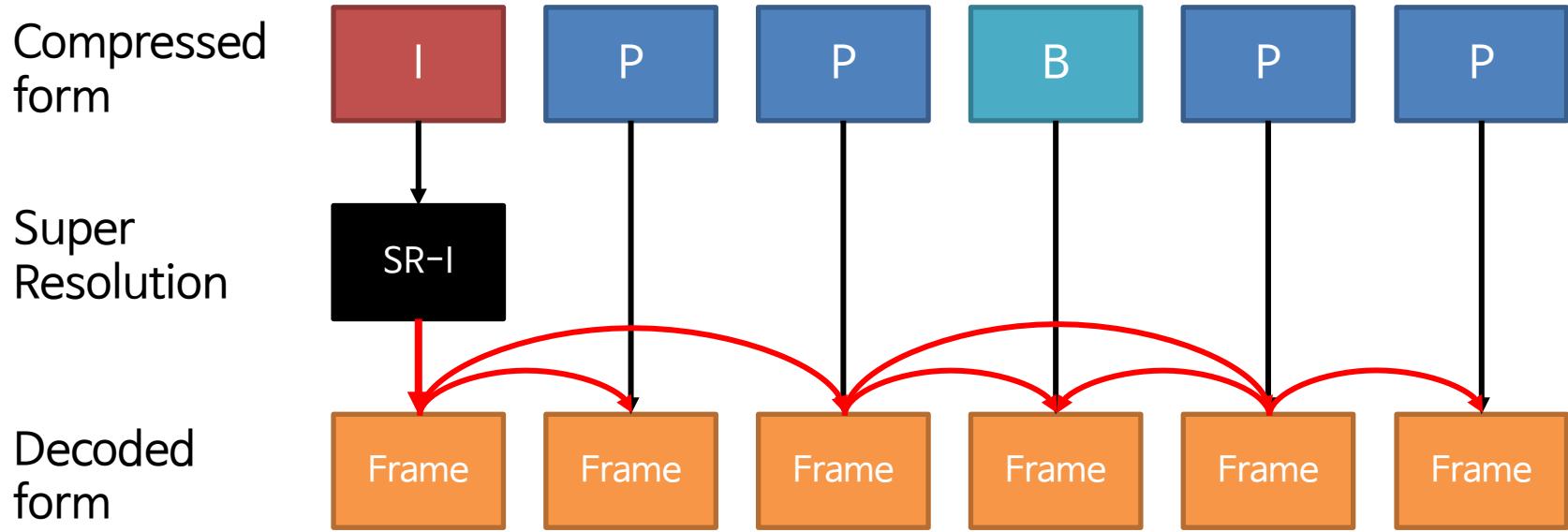
**Performing super resolution for every frame**

SR cannot be done in a frame interval  
High computation overhead

Frame interval	0.03s
VDSR	0.1s
SRCNN	2s
A+	0.9s

# Approach

Our approach: perform super resolution on **I-frame only**



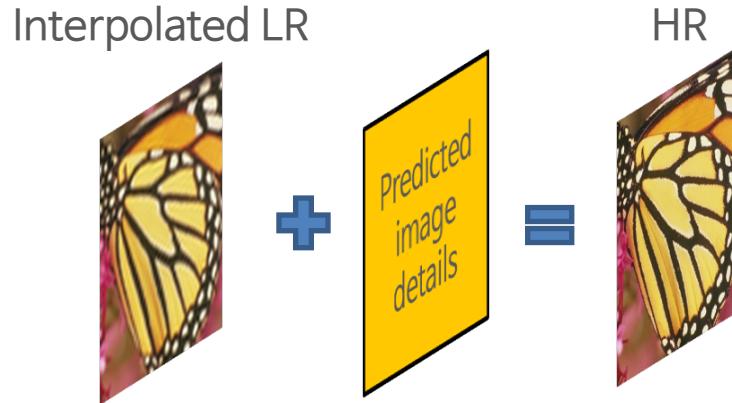
**Performing super resolution for I-frame only**

SR can be done in GOP interval (0.5s ~ 2s)

All frames are affected by SR I-frame (as they reference it)

# Learning based SR - Algorithm (VDSR)

- Learn residual only for fast convergence
- Input : interpolated low resolution image

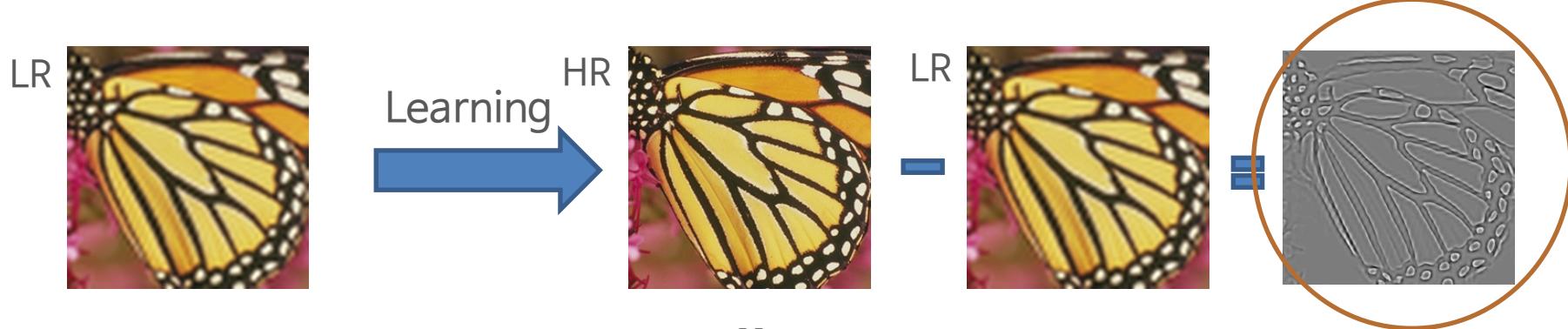


- Residual image learning



# Learning based SR - Algorithm (VDSR)

- Learn residual only for fast convergence
- Input : interpolated low resolution image
- Residual image learning

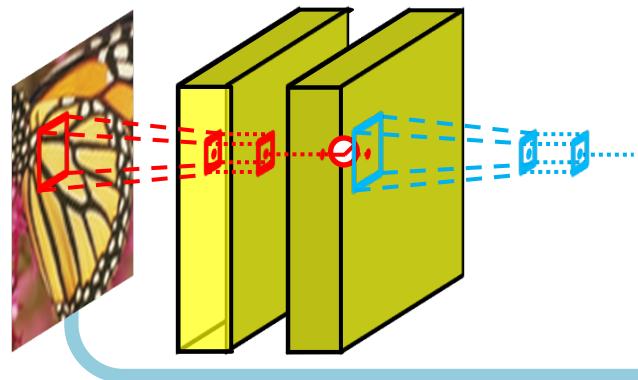


- Training dataset  $\{\mathbf{x}^{(i)}, \mathbf{y}^{(i)}\}_{i=1}^N$
- Define residual image  $\mathbf{r} = \mathbf{y} - \mathbf{x}$
- Goal is to minimize  $\frac{1}{2} \|\mathbf{r} - f(\mathbf{x})\|^2$

x: interpolated LR  
y: HR  
r: residual image  
f: network prediction  
f(x)+x: final image

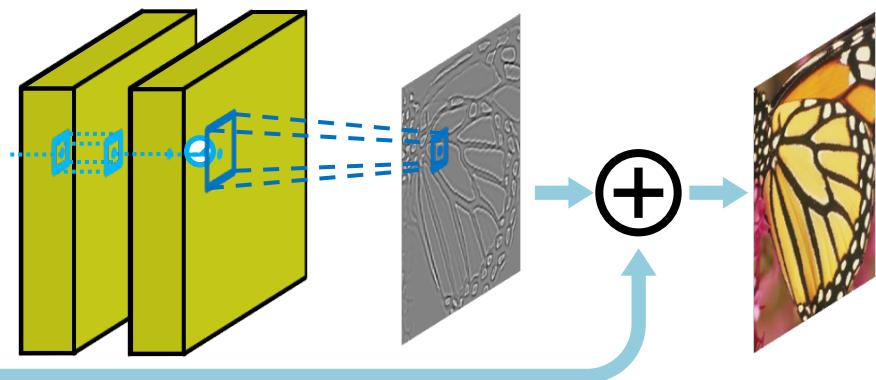
# Learning based SR - Model (VDSR)

Interpolated LR Conv.1 ReLu.1



...

Conv.D-1 ReLu.D-1 learned residual



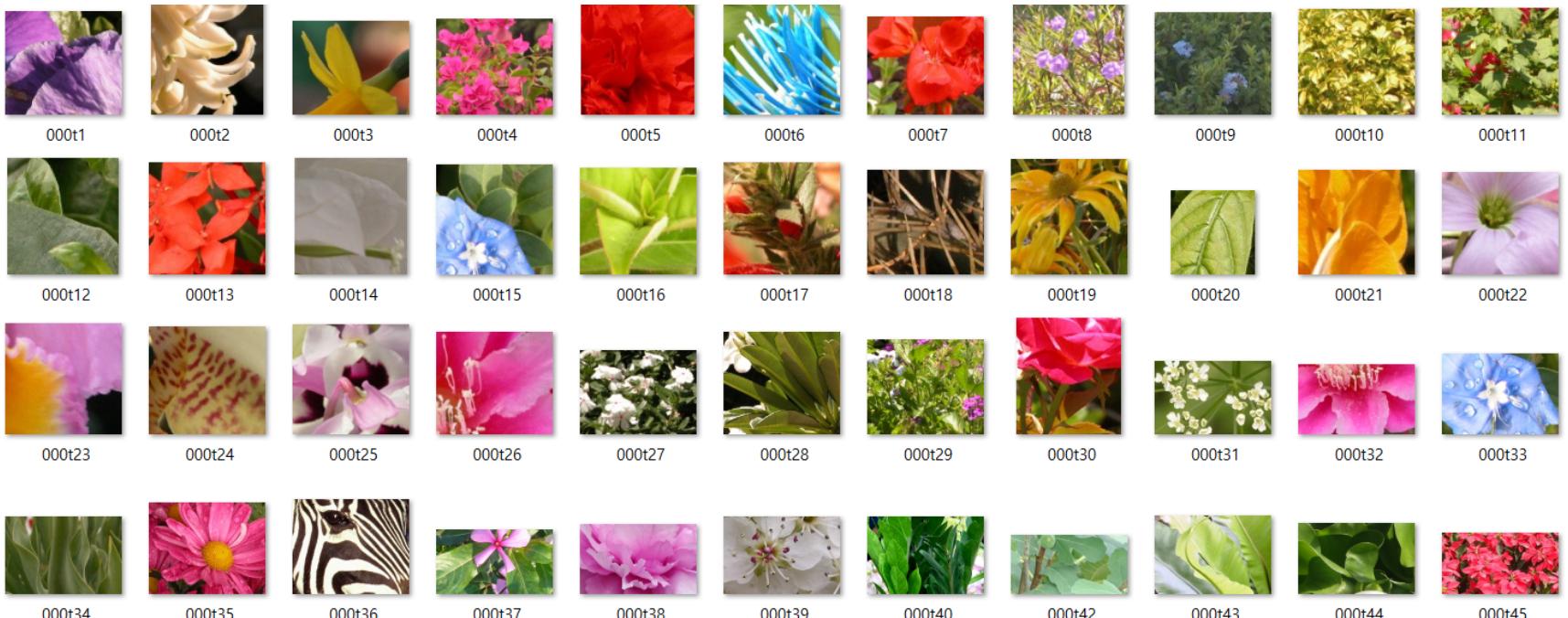
Skip-connection way

- CNN to SR
  - 20 convolutional layers
  - Skip connection to learn residual only
  - No dimension reduction such as pooling

# Learning based SR - Training Data (VDSR)

## Training data

- 291 images with data augmentation (rotation or flip)
  - 91 from Yang et al. [1] + 200 from Berkeley segmentation dataset [2]



[1] Image superresolution via sparse representation by Yang et al. TIP, 2010

[2] A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. by Martin et al., ICCV, 2001

# Implementation

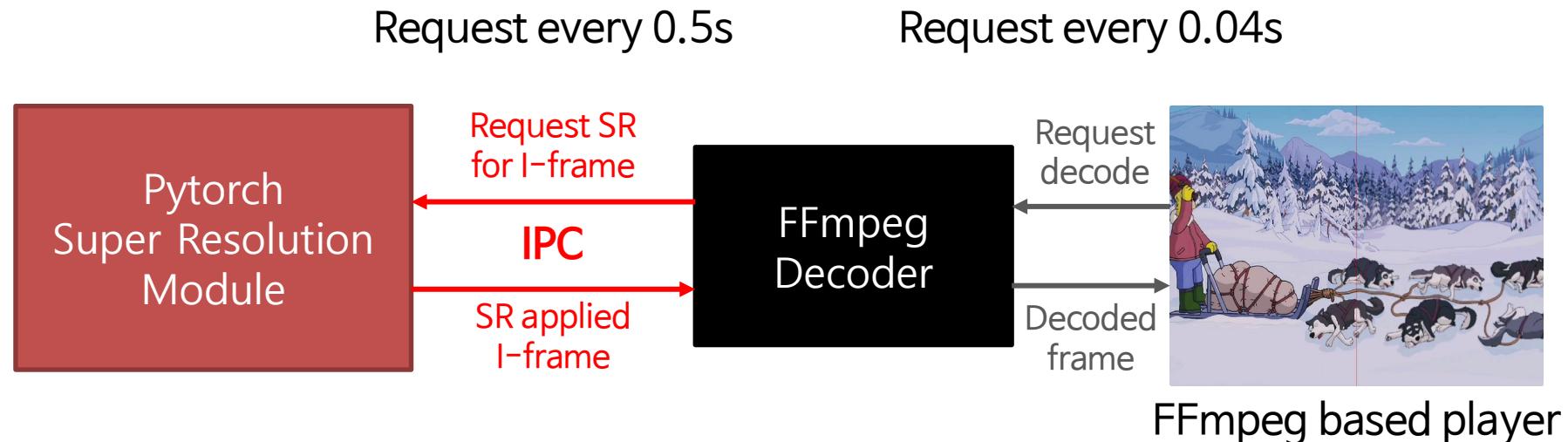
Target movie: all videos with 24 fps, GOP length=12

Movie Player: Simple FFmpeg based player [\[link\]](#)

H.264 Decoder: FFmpeg [\[link\]](#)

SR Module: Pytorch VDSR [\[link\]](#) with pre-trained checkpoint

Communication: Message queue btw SR module / FFmpeg



# Performance Measurement

## 1. Peak Signal-to-Noise Ratio (PSNR)

- Most commonly used to measure the quality of reconstruction of lossy compression codecs
- Commonly used metric for super resolution

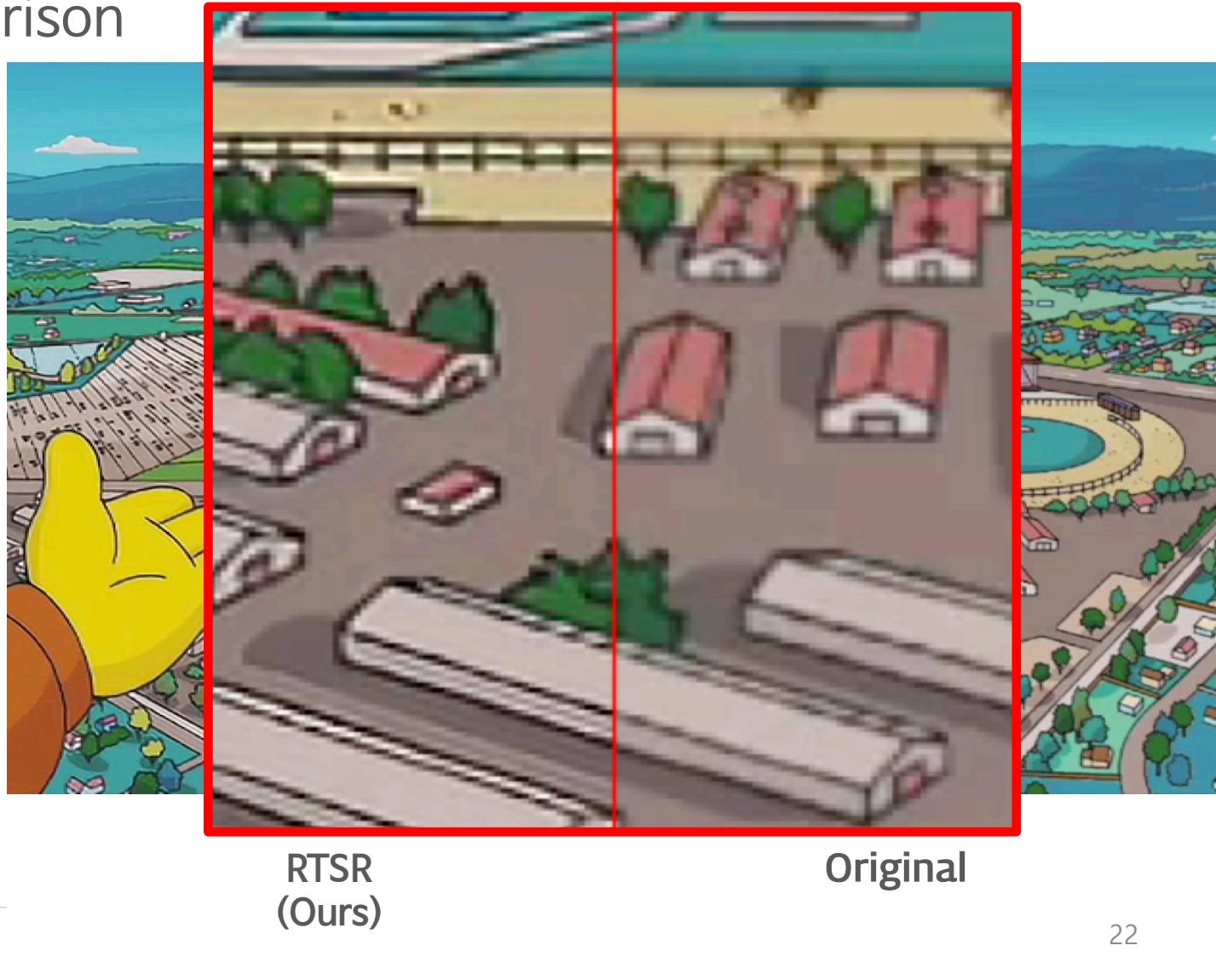
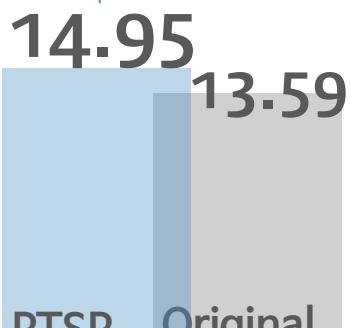
## 2. Time Delay

- We argued that performing super resolution for all frames cannot be done in real-time.
- Measure how the delay is in (1) SR for all frames, (2) ours

# Interpret Results

## PSNR Comparison

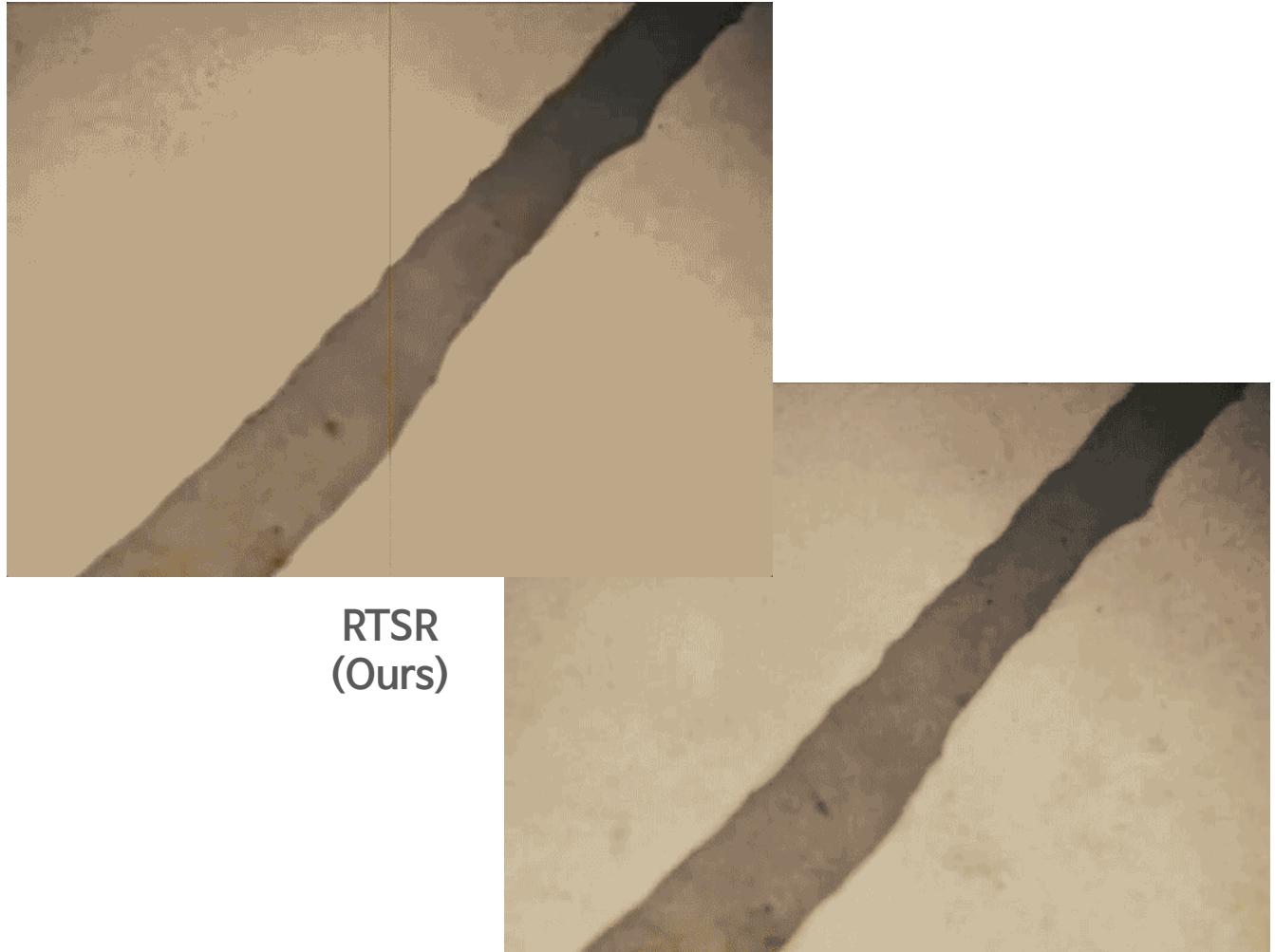
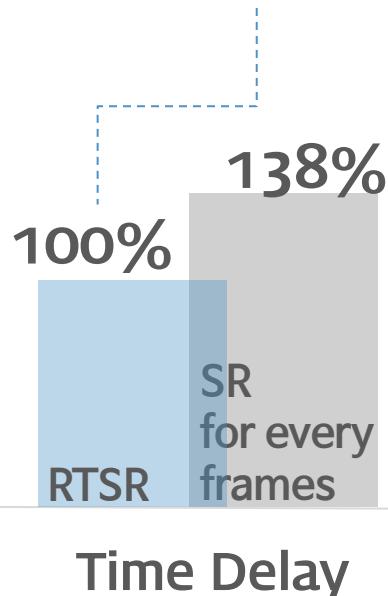
Higher is better



# Interpret Results

## Time Delay Comparison

Playtime compared to  
original video  
Closer to 100% is better



SR for every frames

# Discussion

## 1. Contribution

- Applied SR with Deep Learning in real-time streaming to reconstruct high-resolution videos.
- Our proposed model only applied SR to i-frames, which is outperformed without time-delayed than applied SR to all frames.

## 2. Limitation

- The high quality of reconstructed video is depending on original video sources.

# Demo

## Test Video 1

**THE FOLLOWING PREVIEW HAS BEEN APPROVED FOR  
ALL AUDIENCES  
BY THE MOTION PICTURE ASSOCIATION OF AMERICA**

[www.filmratings.com](http://www.filmratings.com)

RTSR (ours)

[www.mpaa.org](http://www.mpaa.org)

Original

# Demo

## Test Video 2



RTSR (ours)

Original

# Thank you.

Q&A