

# Light Field Image Coding Using VVC standard and View Synthesis based on Dual Discriminator GAN

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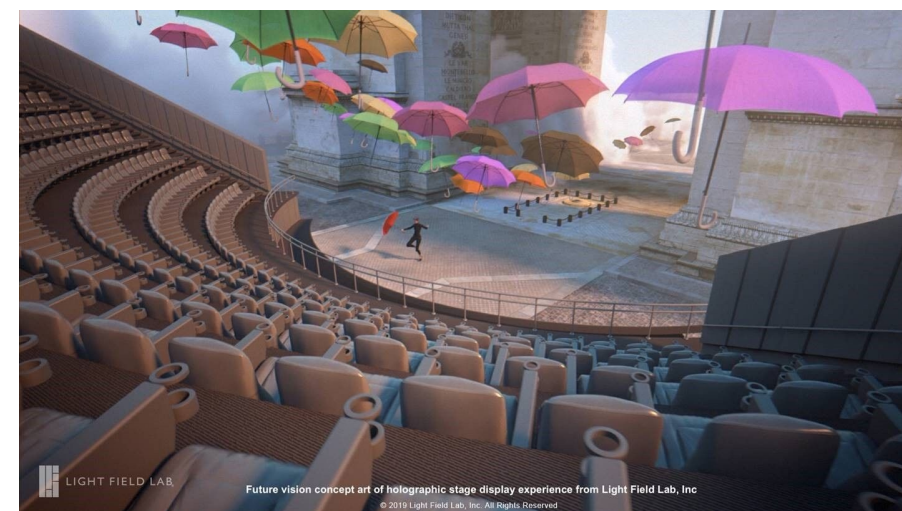
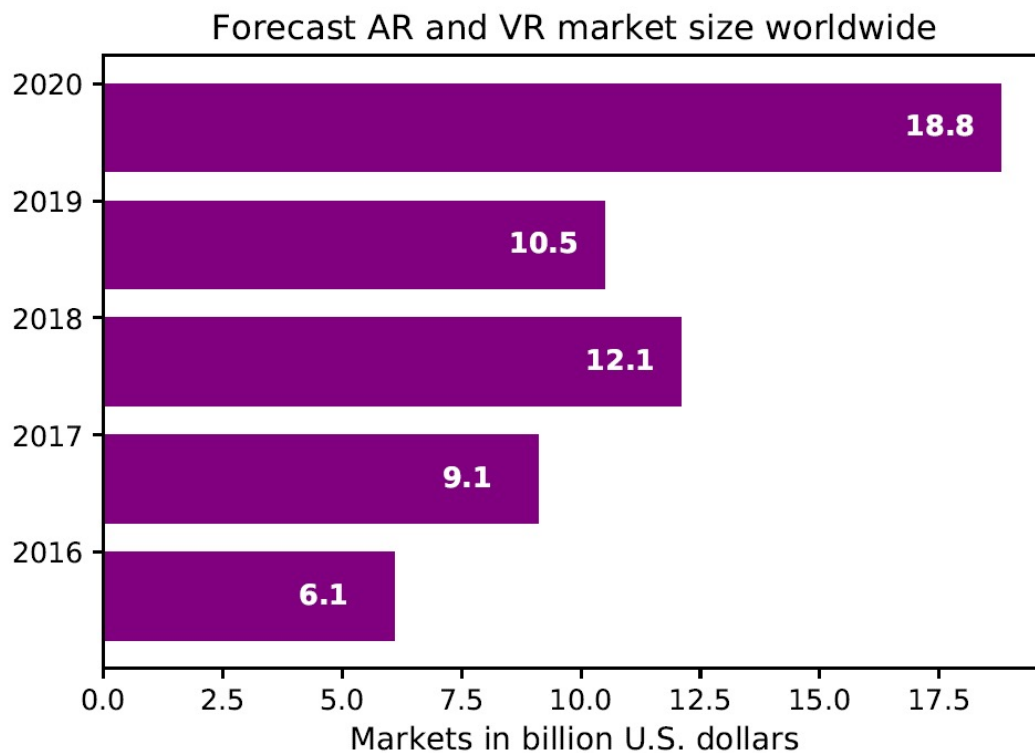
**CLIM 2 workshop – INRIA Rennes**

September 30th 2021

# Outline

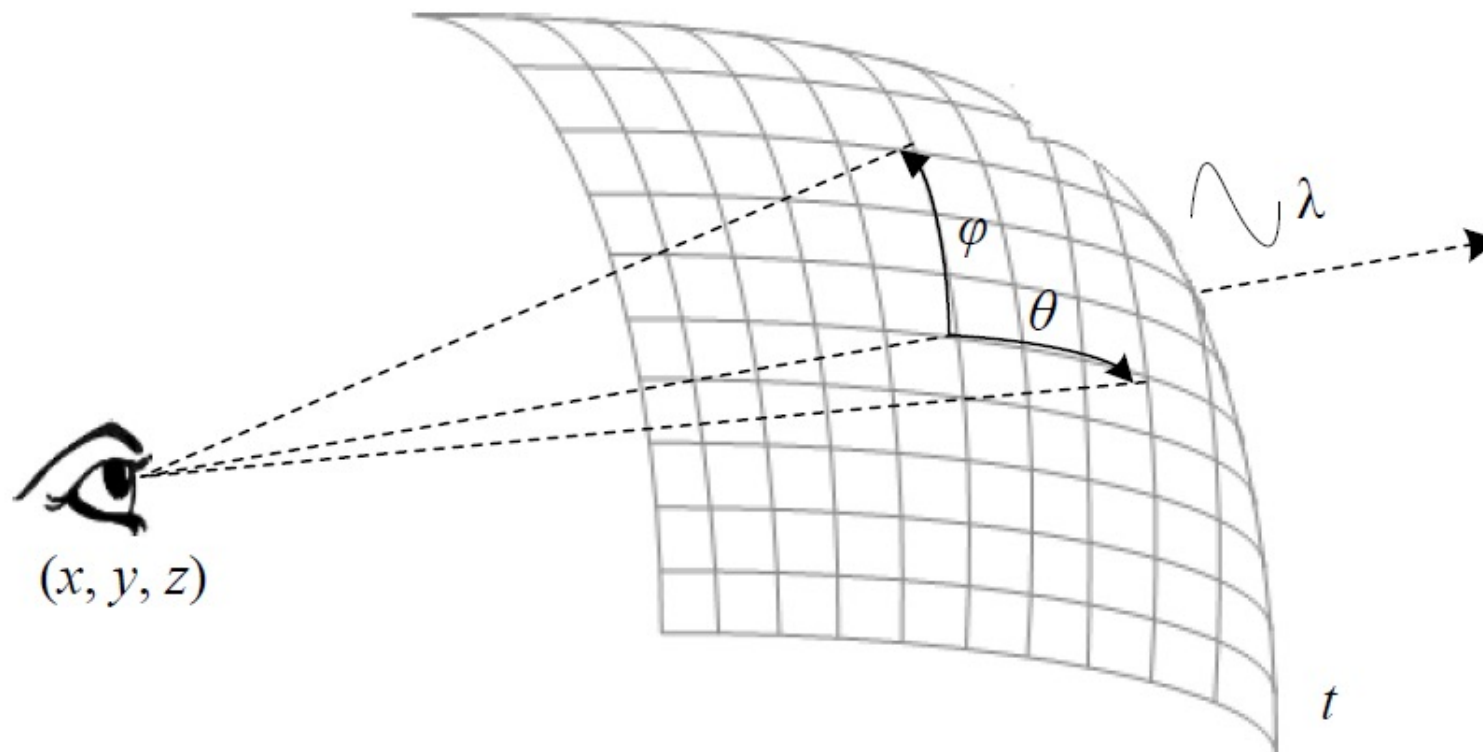
- **Context & challenges**
- Related work
- Proposed solution
- Experimental Results
- Conclusion

## Augmented Reality (AR) & Virtual Reality (VR) applications



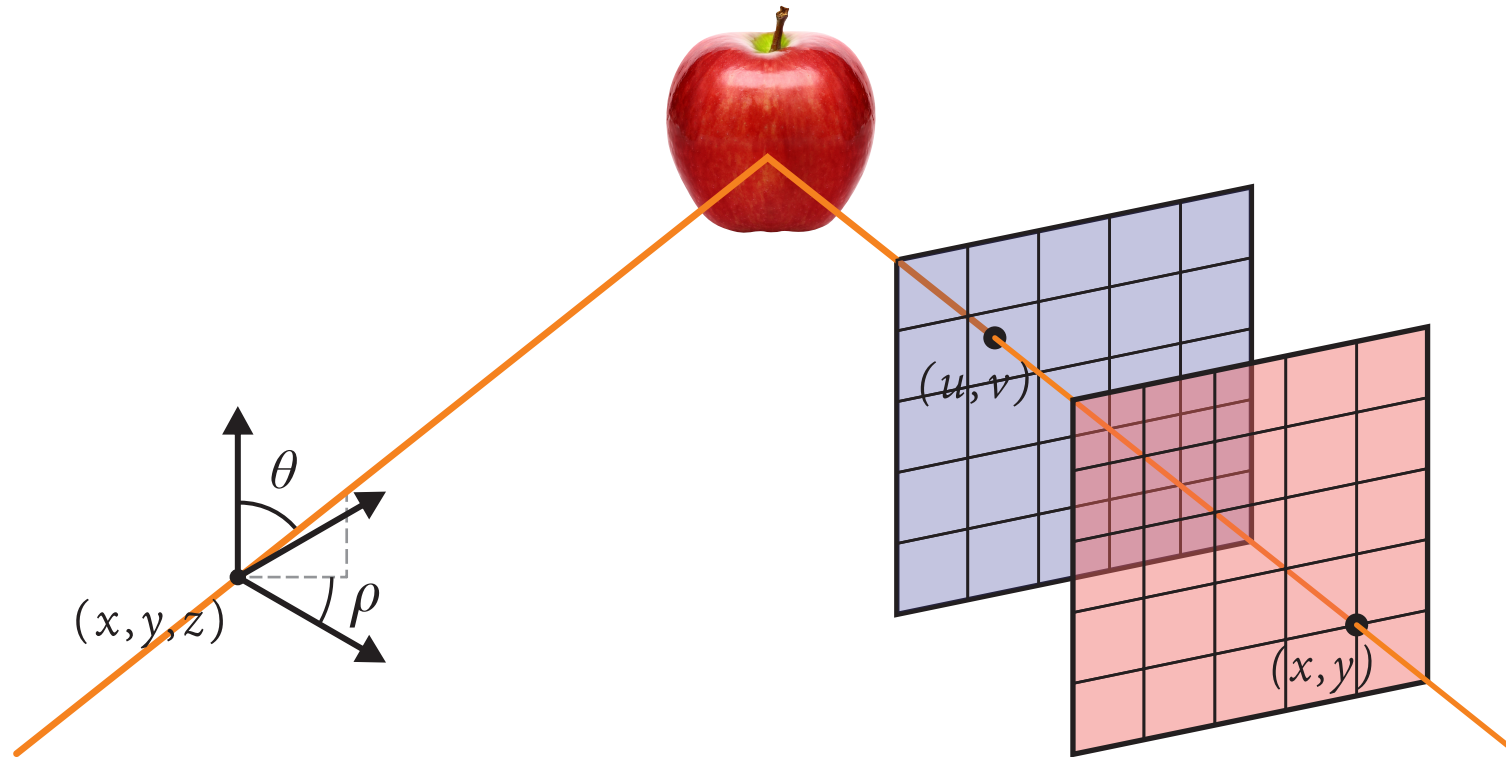
## □ Definition of Light Field

- Seven dimensional function  $L(x, y, z, \theta, \varphi, \lambda, t)$

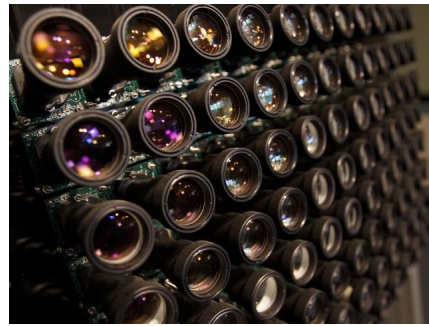


## □ Definition of Light Field

- Seven dimensional function  $L(x, y, z, \theta, \varphi, \lambda, t)$
- Four dimensional function with two parallel planes  $L(u, v, t, s)$



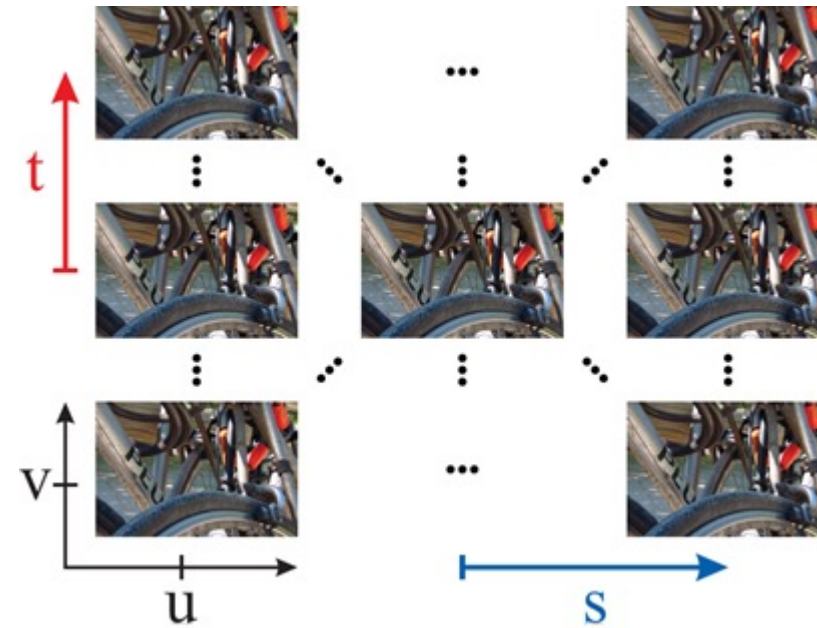
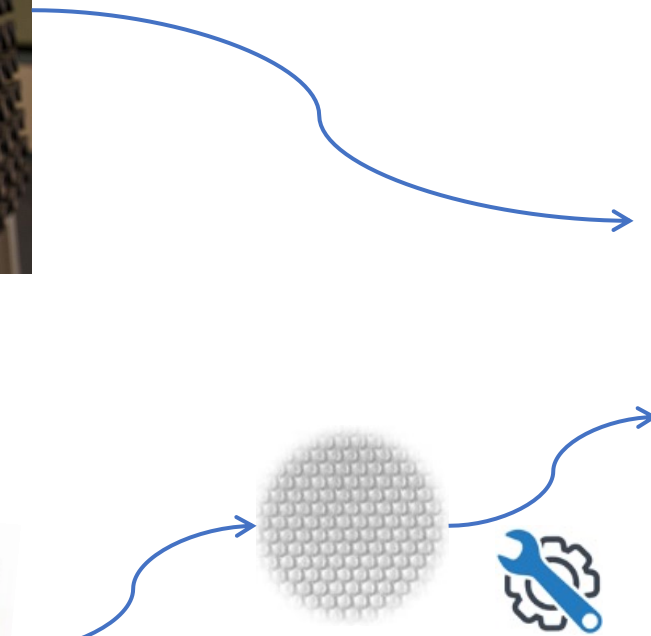
## □ Light Field image acquisition and representation



Multi camera

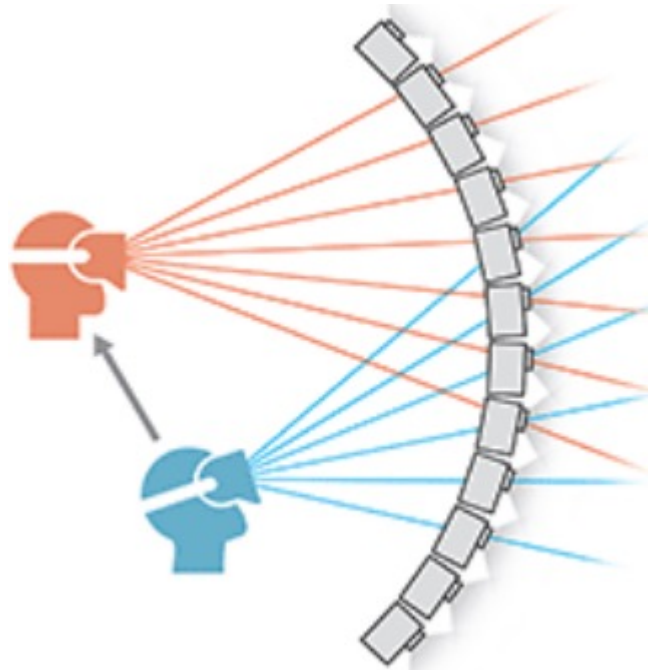


Plenoptic camera



## □ Advantages of Light Field technology

- Refocusing capability after capture
- Change of perspective (view point)
- Field display for VR



## ❑ Limitations of Light Field technology

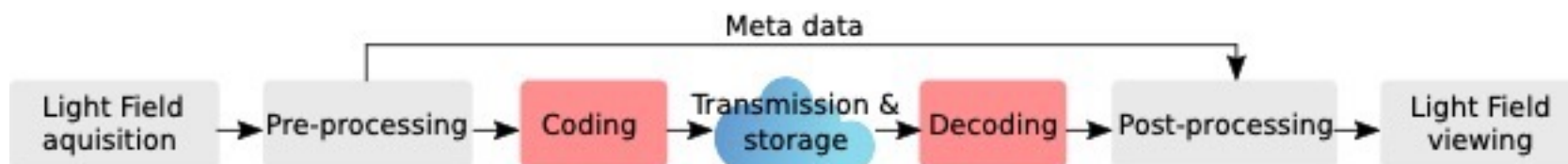
- Very large amount of data for storage and transmission
- High computational processing and energy
- Highly redundant data



1 LF image Lytro Illum Camera requires 1.5 Gbits

## ❑ Objective

- Propose an efficient and low complexity coding solution for LF images

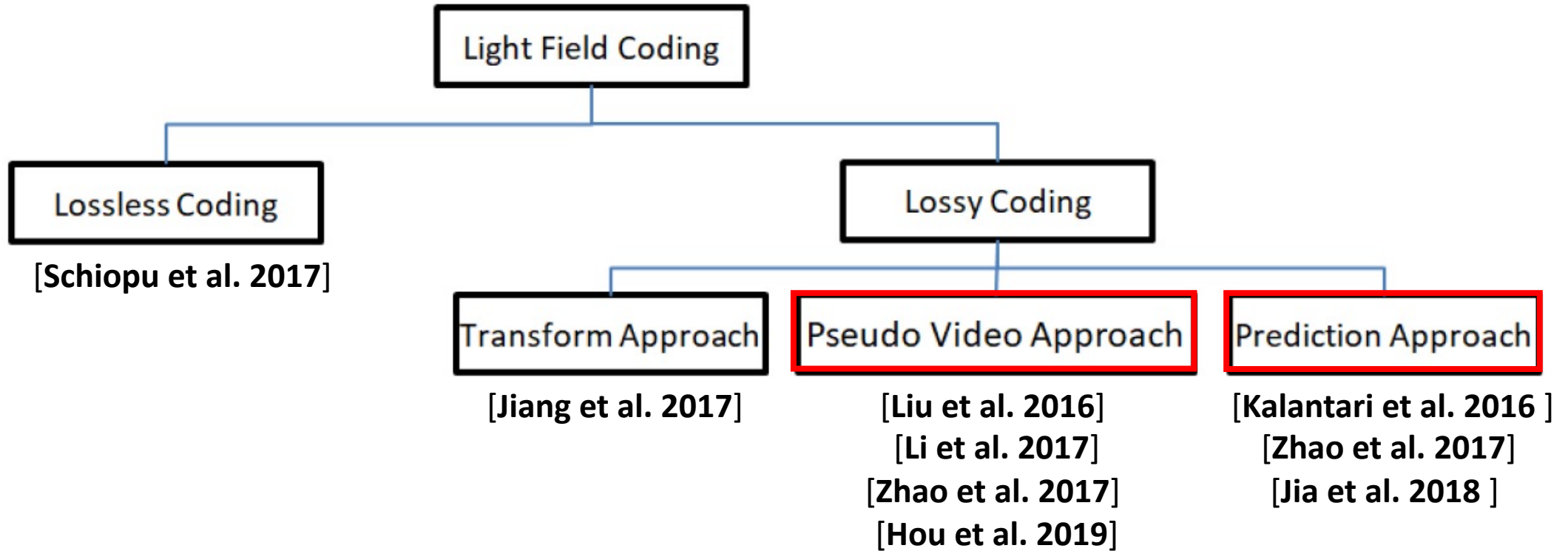




# Outline

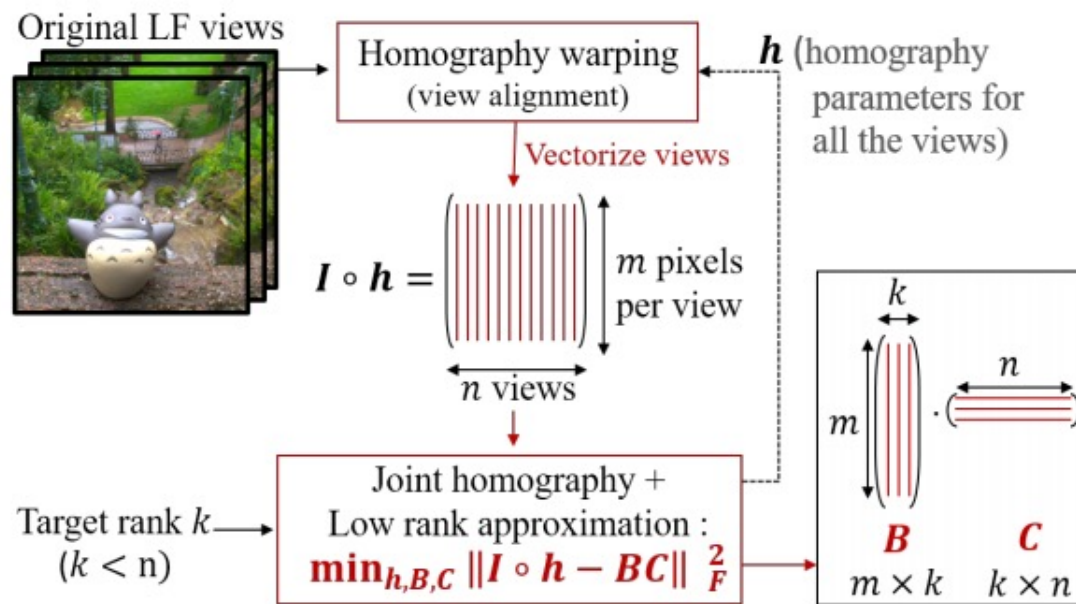
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## □ State-of-the-art of Light Field Image Compression



❑ **LF Compression with Homography-based Low Rank Approximation (HLRA) [Jiang et al. 2017]**

- Based joint optimization of multiple homographies and **LRA**<sup>1</sup>
- Using homography in order to reduce the error produced by **LRA** between **SAI**<sup>2</sup>

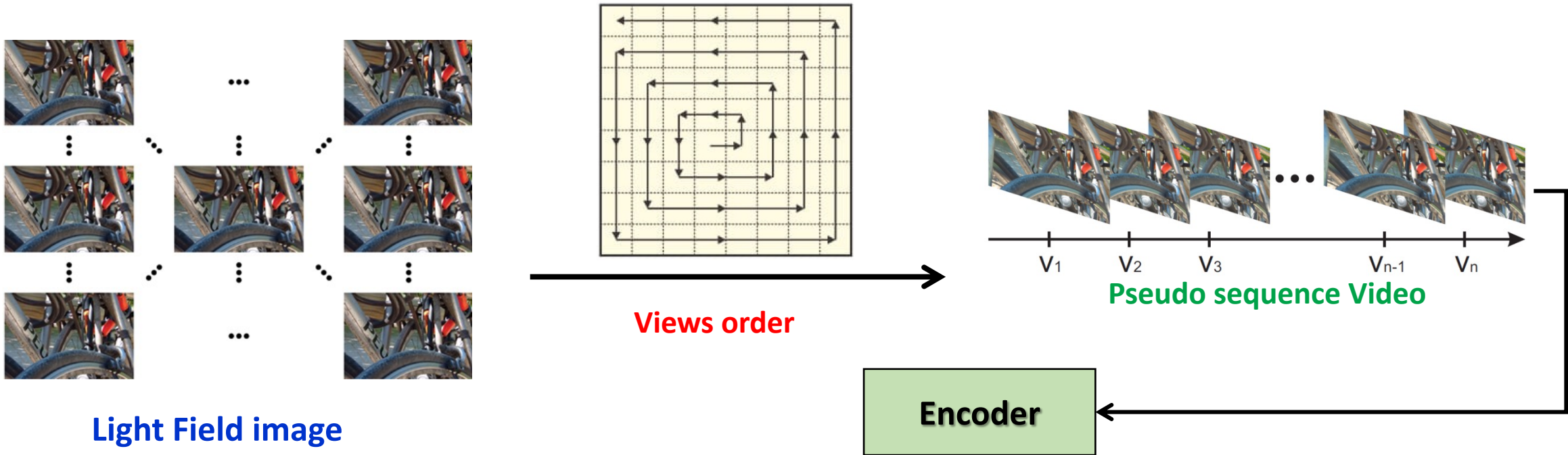


Overview diagram of the HLRA method.

- 1: Low Rank Approximation
- 2: Sub-Aperture Images

## □ State-of-the-art of Light Field Image Compression [Lui et al. 2016]

- Pseudo video coding approach



□ LF image coding via linear approximation [Zhao et al. 2017]

$S_R \in \mathbb{R}^{mn \times M}$ , consists of M vectorized references views in  $S_A$

$s_b$  is the target view to be recovered

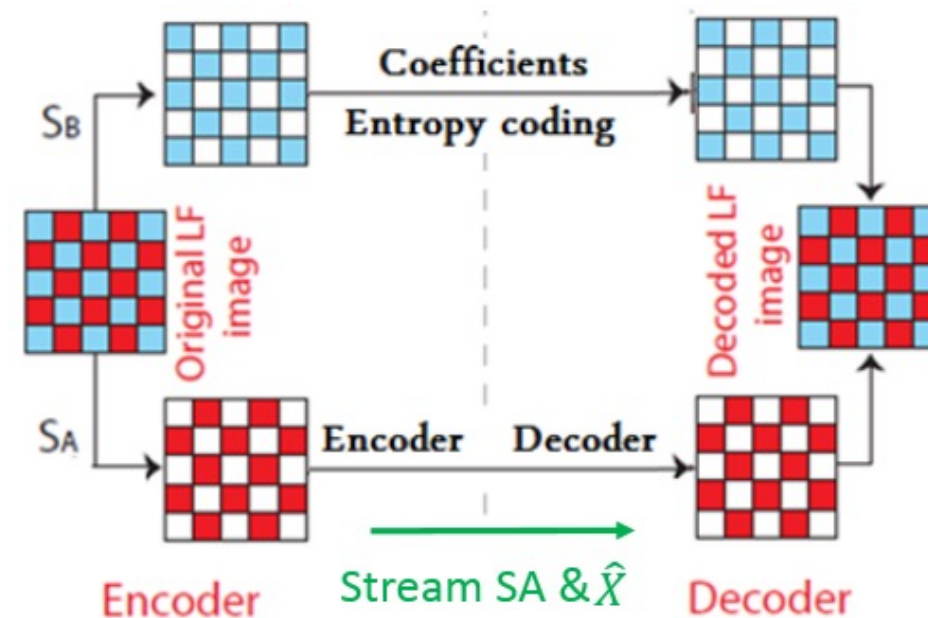
$$X_b = \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \dots \\ \dots \\ a_M \end{bmatrix} \in \mathbb{R}^M$$

$$S_R = \left( \begin{array}{c} \text{mn pixels} \\ \text{per view} \end{array} \right)$$

M vectorized views

$$\min \|X_b\|_1$$

subject to  $\|S_R \cdot X_b - s_b\|_2 \leq \epsilon$



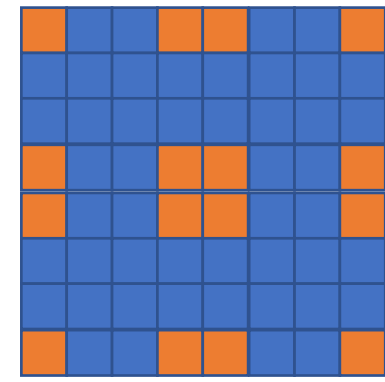
Linear Approximation (LA) Coding Scheme [Zhao et al. 2017]

# Outline

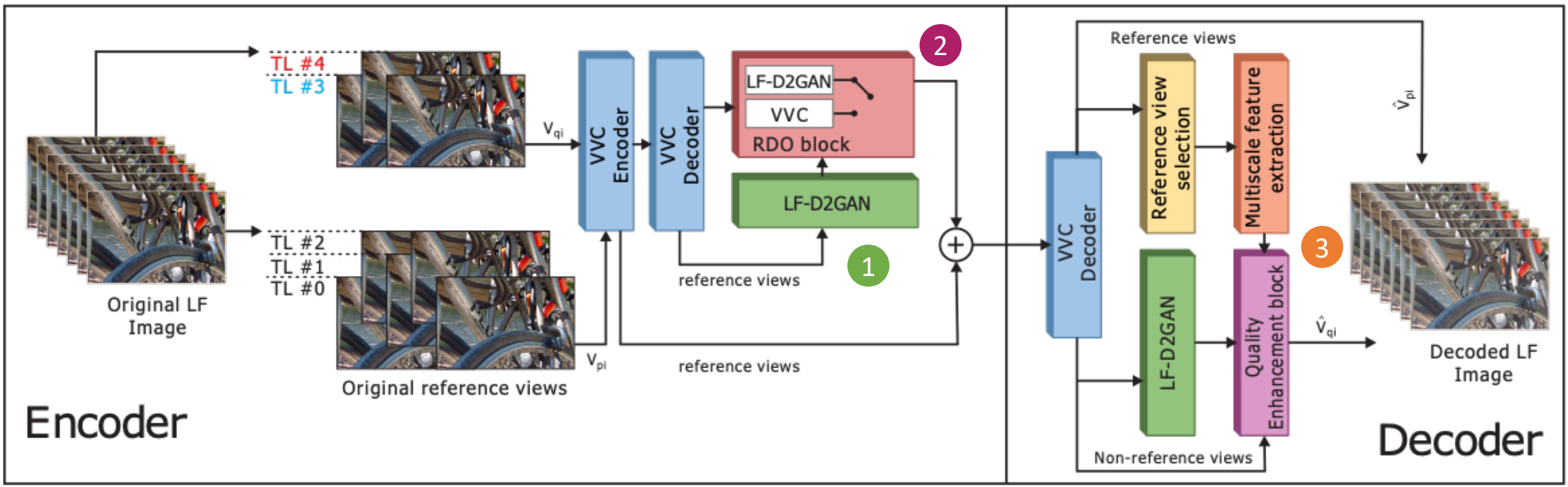
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# Proposed Solution (1/8)

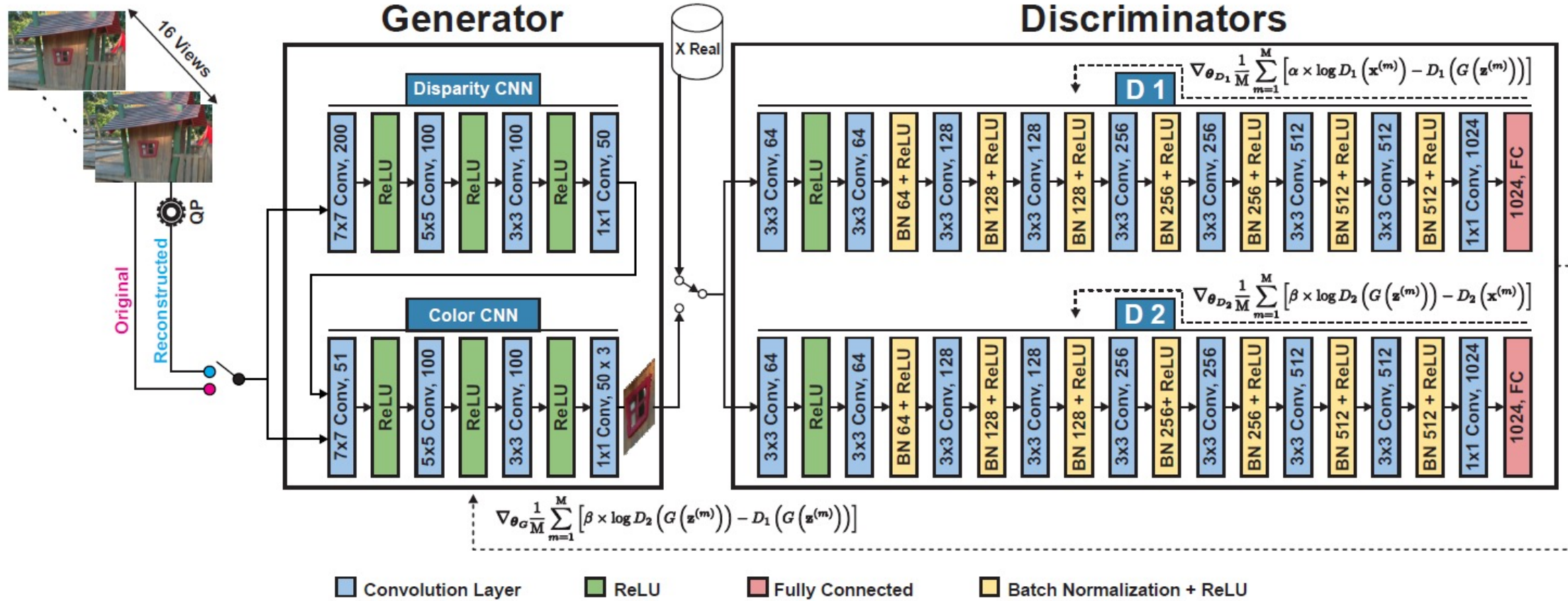
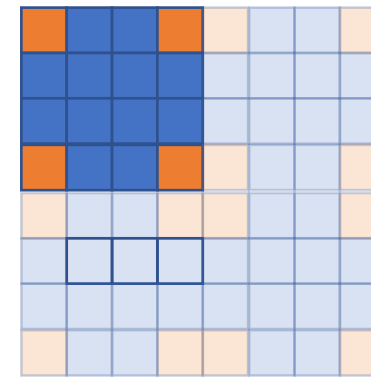
16 reference views  
48 other views



Overall scheme of the proposed solution



## Architecture of the view synthesis block D2GAN



Nguyen et al., [Dual Discriminator Generative Adversarial Nets](#), 31st Conference on Neural Information Processing System (NIPS 2017), USA.



## □ D2GAN Loss function formulation

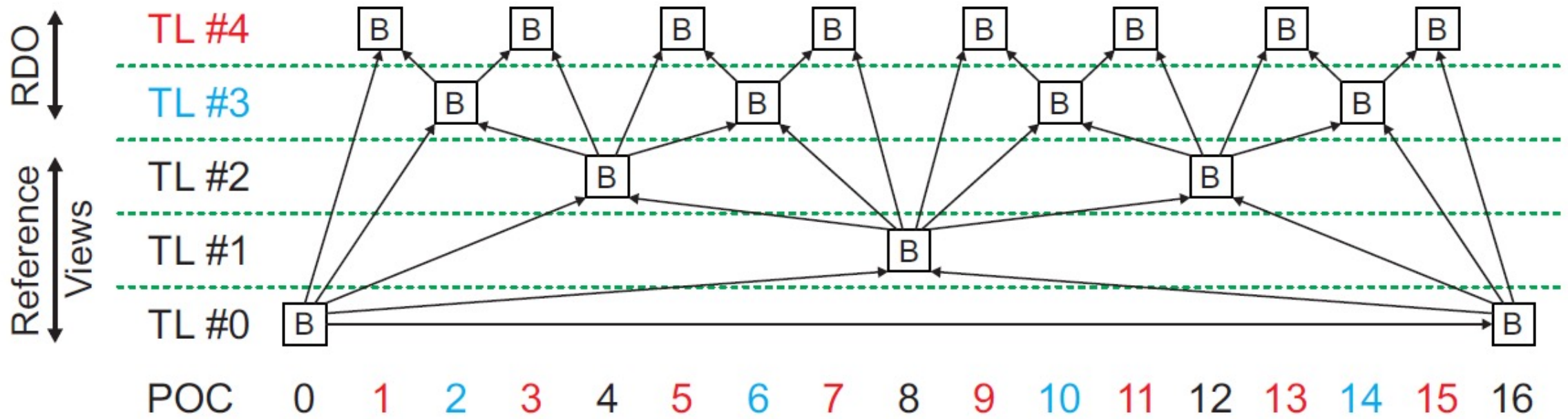
$$\min_G \max_{D1, D2} \mathcal{L}(G, D1, D2)$$

### □ Three player minimax optimization game:

- Discriminators maximizing its reward  $V(G, D1, D2)$
- Generator minimizing Discriminators reward (or maximize its loss)

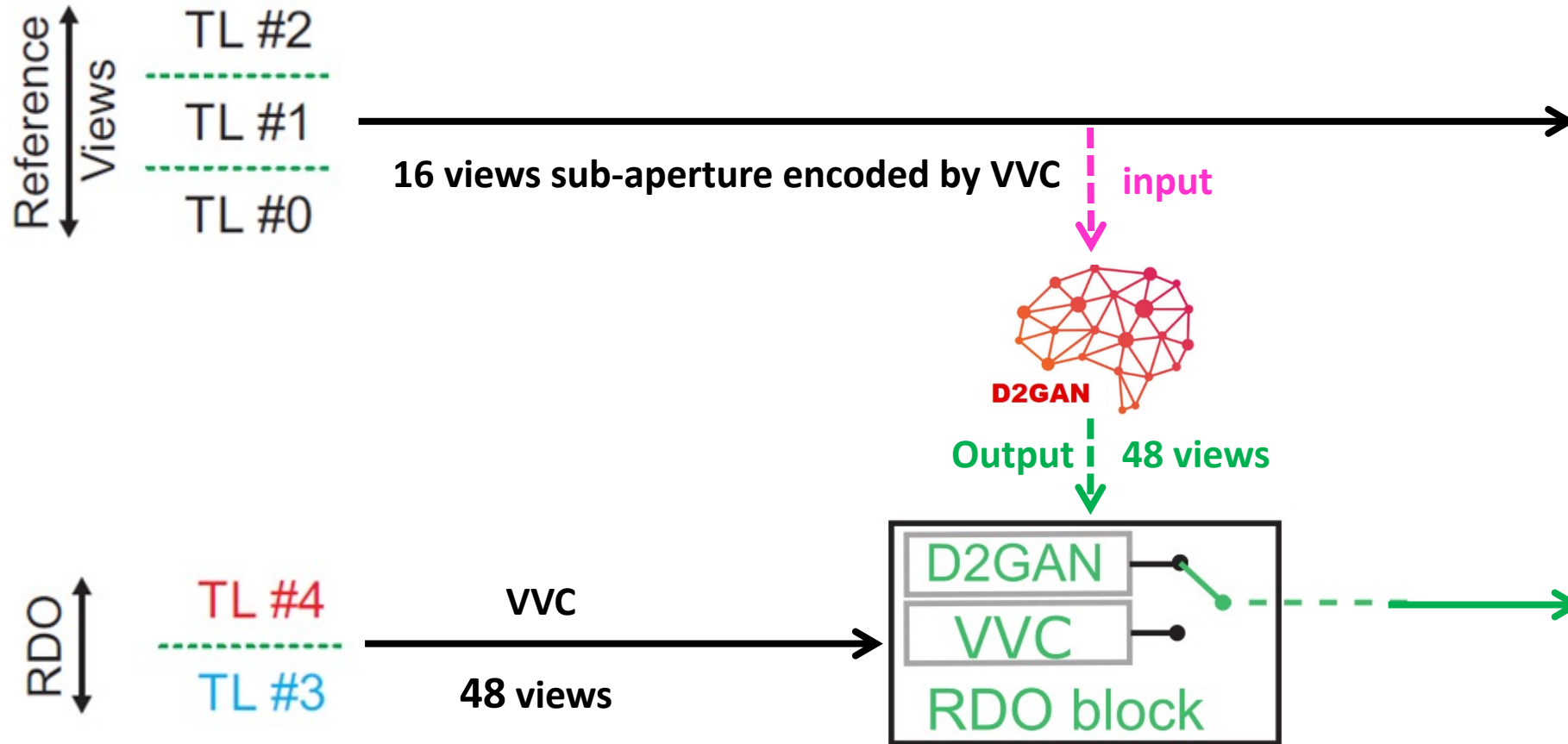
$$\begin{aligned} \mathcal{L}(G, D_1, D_2) = & \alpha \mathbb{E}_{x \sim P_{data}} [\log D_1(x)] + \mathbb{E}_{z \sim P_z} [-D_1(G(z))] \\ & + \mathbb{E}_{x \sim P_{data}} [-D_2(x)] + \beta \mathbb{E}_{z \sim P_z} [\log D_2(G(z))] \end{aligned}$$

## Versatile Video Coding (VVC) hierarchical coding architecture



Hierarchical prediction structure in VVC - One GOP is shown.

## □ The proposed strategy



## □ Rate distortion optimization

**Algorithm 2:** Algorithm of the RDO between VVC and D2GAN

**Require:**  $\mathcal{J} \leftarrow \{ \forall m, \forall v \in TL\#[3 \text{ or } 4], \mathcal{J} = D + \lambda R \}$

m: method {VVC, D2GAN}

for all  $v \in TL\#4$  do

if  $\mathcal{J}(VVC) < \mathcal{J}(D2GAN)$  then

Encode  $v$  by VVC

flag( $v$ )  $\leftarrow$  false

else

generate  $v$  by D2GAN

flag( $v$ )  $\leftarrow$  true

end if

end for

for all  $v \in TL\#3$  do

if  $\mathcal{J}(VVC) < \mathcal{J}(D2GAN)$  then

Encode  $v$  by VVC

flag( $v$ )  $\leftarrow$  false

else {flag(previous( $v$ )) and flag(next( $v$ ))}

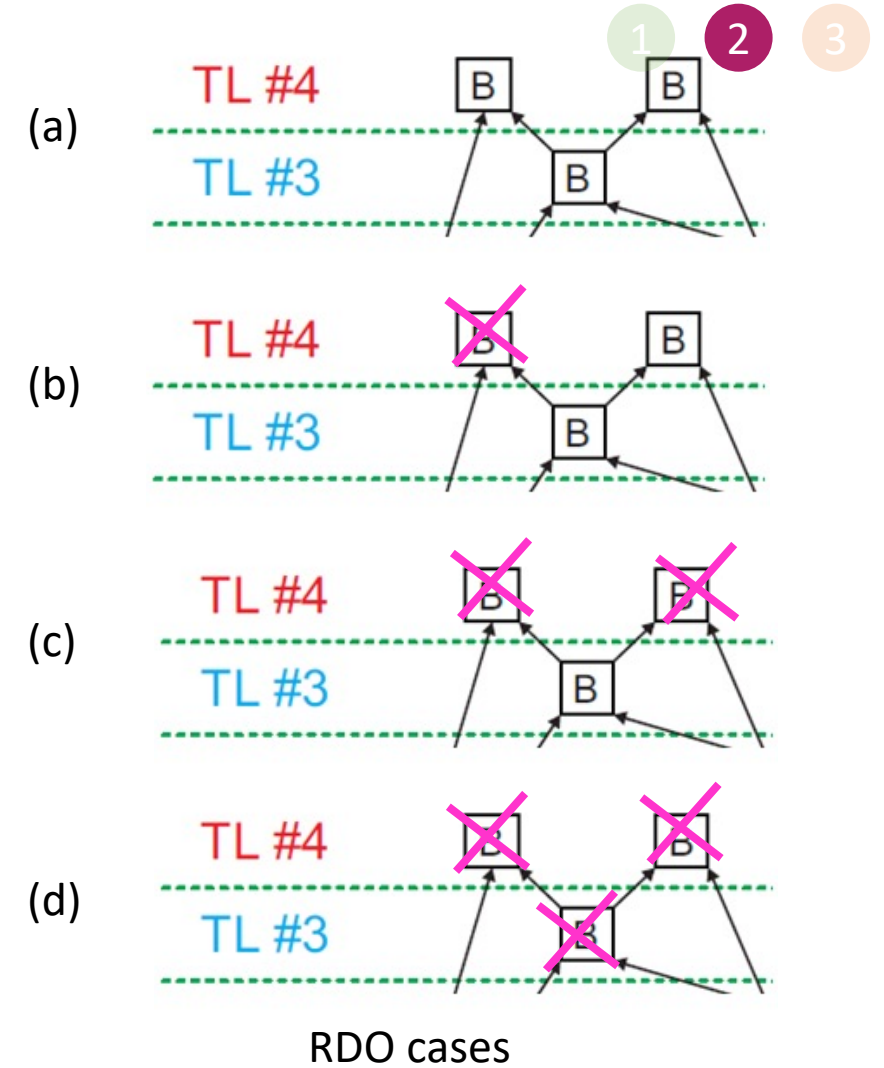
generate  $v$  by D2GAN

flag( $v$ )  $\leftarrow$  true

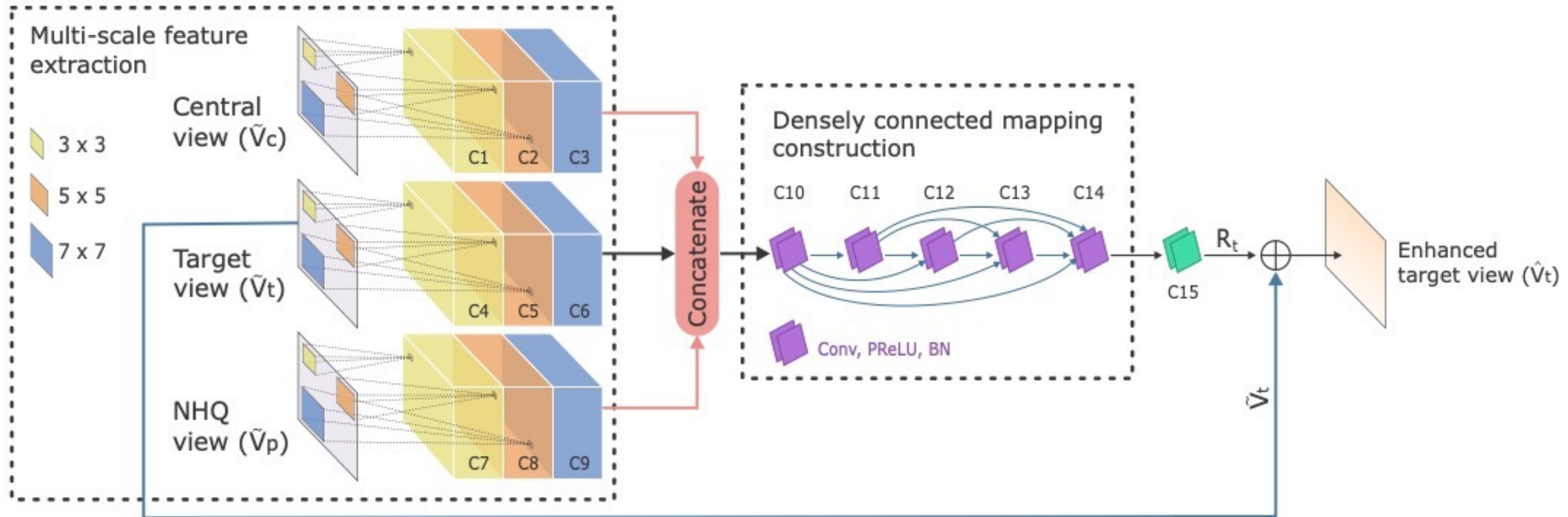
end if

end for

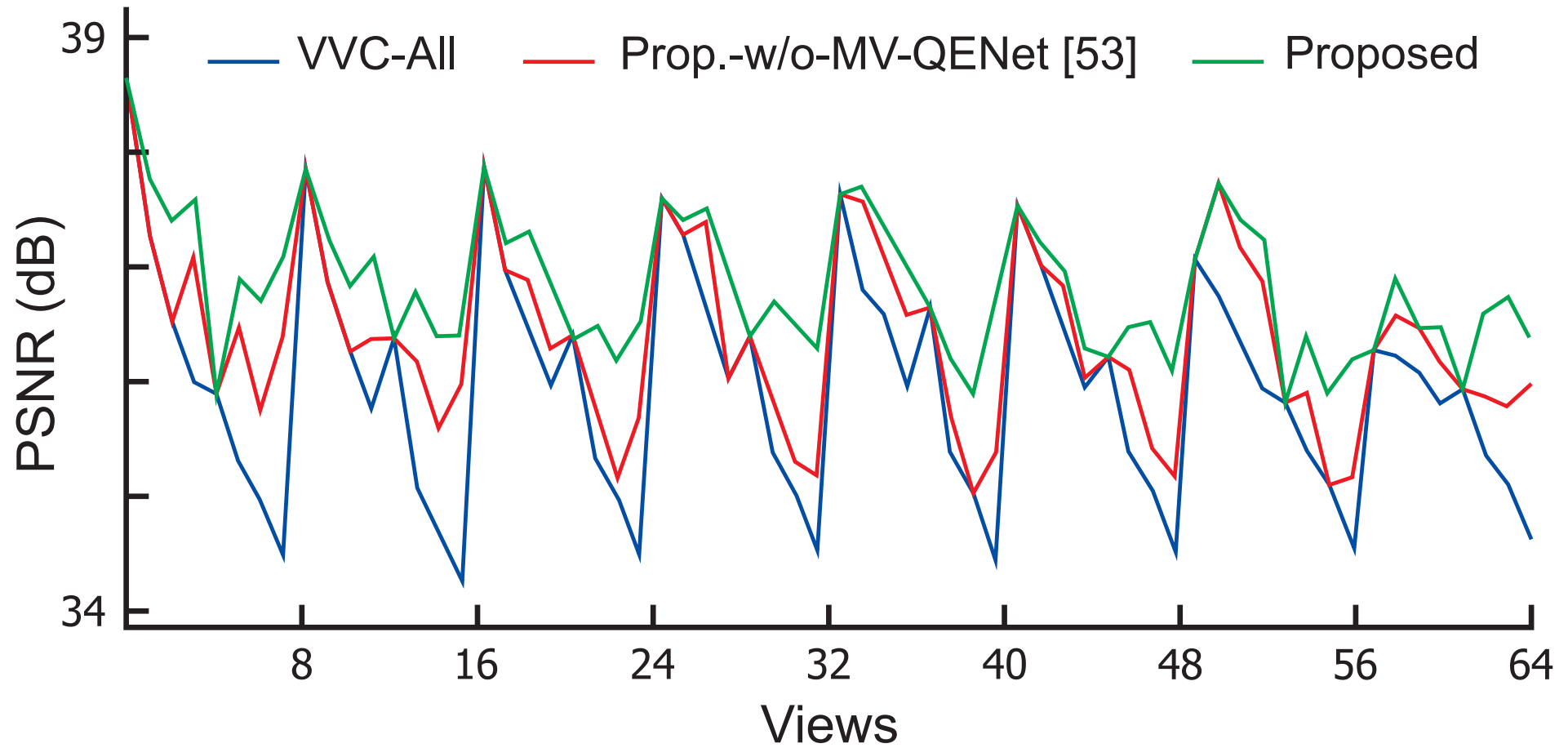
$$J = D + \lambda R$$



## Quality Enhancement Module: MV-QENet



□ MV-QENet performance



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## □ For the training phase, 140 LF images (8x8 views) have been selected:

- EPFL dataset (70 images), Stanford university LF dataset (50 images), HCI dataset(20 images).
- Each sub aperture are splitting into patches (60x60 pix).
- Trained with more than 150,000 patches.

## □ 2D-AN Training Parameters

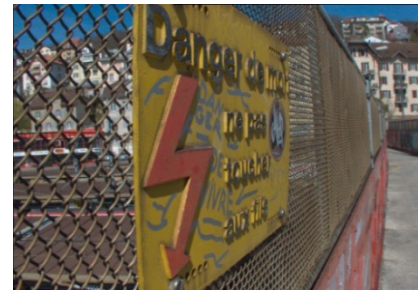
|   |  |
|---|--|
| <b>Mini-batches size</b>                        | 10   |
| <b>ADAM solver</b>                              | $\beta_1 = 0.9$ , $\beta_2 = 0.999$ and $\alpha_{Adam} = 0.0001$ |
| <b>Learning rate</b>                            | 0.0001   |
| <b>Activation function</b>                      | Relu   |
| <b>Regularization coefficients of D1 and D2</b> | $\alpha_{reg} = 0.2$ and $\beta_{reg} = 0.2$                     |



☐ 9 testing LF images

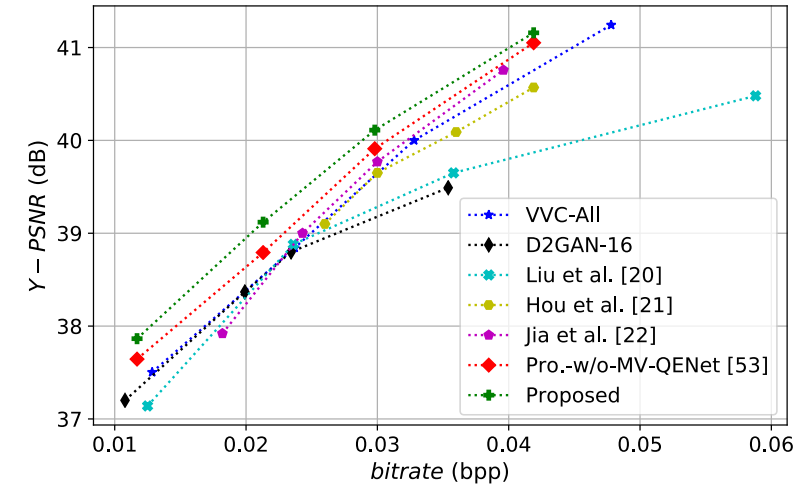
- EPFL dataset (6 images), Stanford university LF dataset (1 images), HCI dataset(2 images).

Central perspective view from each **LF** image used in the test

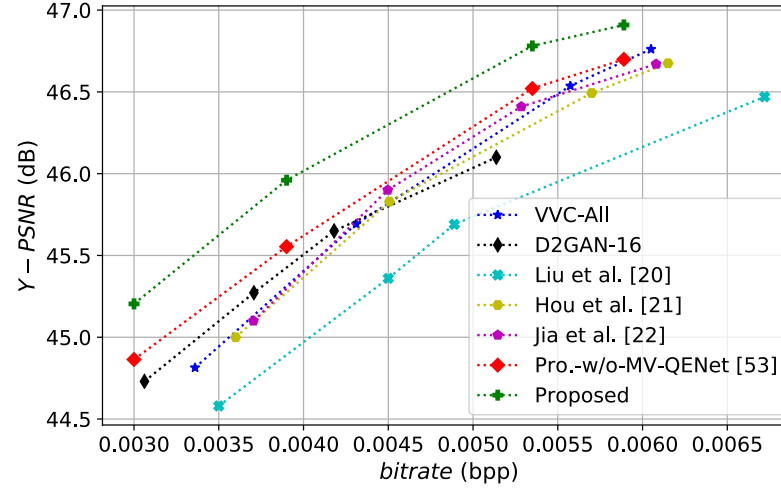


## RD curves of the 5 considered solutions for the 6 LF images

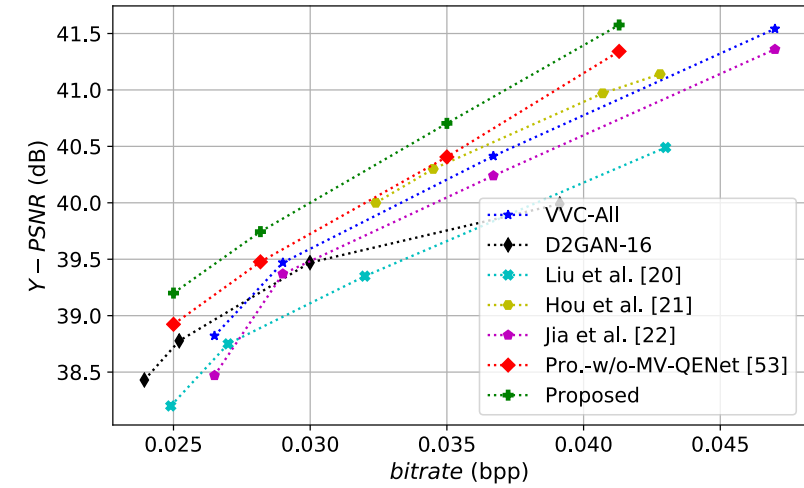
Danger de Mort



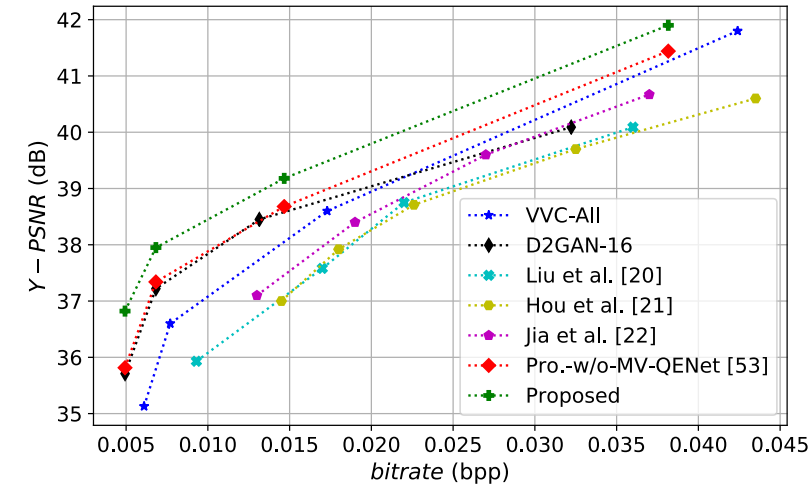
AnkylosaurusDiplodocus1



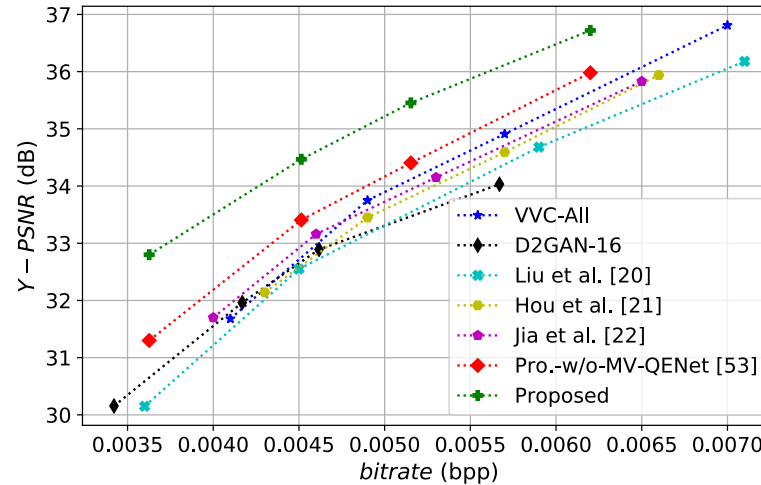
Flowers



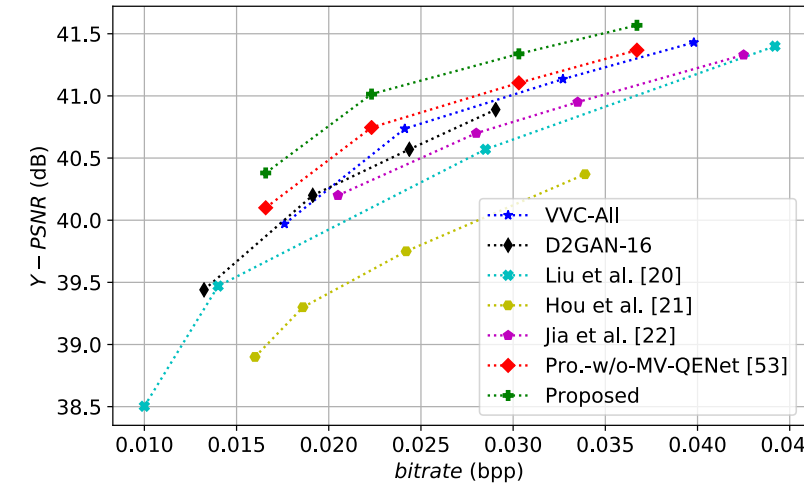
Aloe



Bedroom



Desktop

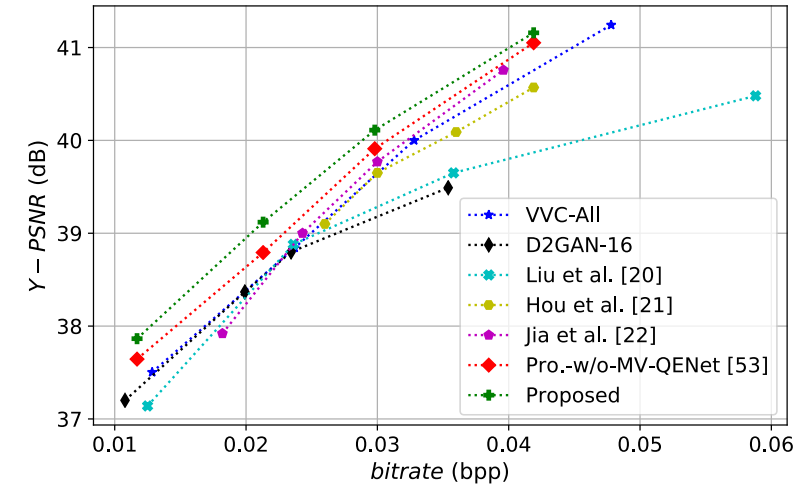


□ BD-BR and BD-PSNR gains calculated against anchor method described in [Lui et al. 2016].

| Image                      | BD-BR versus [Lui et al. 2016] |         |                   |         |                   |         |               |             |                |             |
|----------------------------|--------------------------------|---------|-------------------|---------|-------------------|---------|---------------|-------------|----------------|-------------|
|                            | VVC-All                        |         | [Jia et al. 2018] |         | [Hou et al. 2019] |         | Ours w/o QE   |             | Ours           |             |
|                            | BD-BR                          | BD-PSNR | BD-BR             | BD-PSNR | BD-BR             | BD-PSNR | BD-BR         | BD-PSNR     | BD-BR          | BD-PSNR     |
| <i>Bikes</i>               | -11.7%                         | 0.72    | -6.3%             | 0.48    | -6.9%             | 0.49    | <b>-22.4%</b> | <b>0.96</b> | <b>-31.56%</b> | <b>1.19</b> |
| <i>DangerDeMort</i>        | -7.8%                          | 0.22    | -10.8%            | 0.28    | -8.7%             | 0.26    | <b>-16.5%</b> | <b>0.4</b>  | <b>-25.69%</b> | <b>0.78</b> |
| <i>Flowers</i>             | -12.3%                         | 0.56    | -11.9%            | 0.54    | -16.2%            | 0.72    | <b>-16.6%</b> | <b>0.74</b> | <b>-23.66%</b> | <b>1.03</b> |
| <i>Ankylosaurus Dip1</i>   | -13.2%                         | 0.44    | -14.9%            | -0.72   | -12.3%            | 0.39    | <b>-18.0%</b> | <b>0.57</b> | <b>-31.17%</b> | <b>1.15</b> |
| <i>Aloe</i>                | -26.4%                         | 0.85    | -9.1%             | 0.31    | -2.46%            | -0.12   | <b>-42.3%</b> | <b>1.23</b> | <b>-56.59%</b> | <b>1.84</b> |
| <i>StonePillarsOutside</i> | -18.3%                         | 0.61    | -15.1%            | 0.52    | -11.9%            | 0.28    | <b>-35.6%</b> | <b>0.98</b> | <b>-49.76%</b> | <b>1.42</b> |
| <i>Bedroom</i>             | -5.3%                          | 0.46    | -4.0%             | 0.32    | -2.3%             | 0.18    | <b>-9.5%</b>  | <b>0.85</b> | <b>-24.78%</b> | <b>2.11</b> |
| <i>Desktop</i>             | -19.6%                         | 0.32    | -7.5%             | 0.11    | 44.1%             | -0.61   | <b>-26.3%</b> | <b>0.45</b> | <b>-40.58%</b> | <b>0.79</b> |
| <i>Herbs</i>               | -26.2%                         | 1.14    | -4.4%             | -0.11   | 6.9%              | -0.21   | <b>-29.8%</b> | <b>1.32</b> | <b>-42.25%</b> | <b>1.85</b> |
| <b>Average</b>             | -15.6%                         | 0.59    | -8.3%             | 0.35    | -0.54%            | 0.15    | <b>-24.1%</b> | <b>0.83</b> | <b>-36.22%</b> | <b>1.35</b> |

□ Visual comparison LF images decoded by different codecs

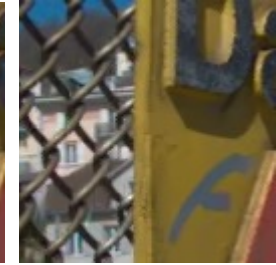
Danger de Mort



[Liu et al.]  
y-psnr: 39.15



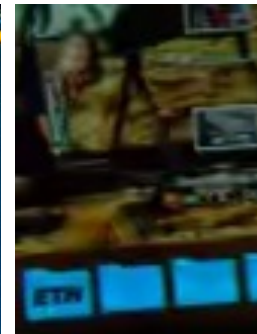
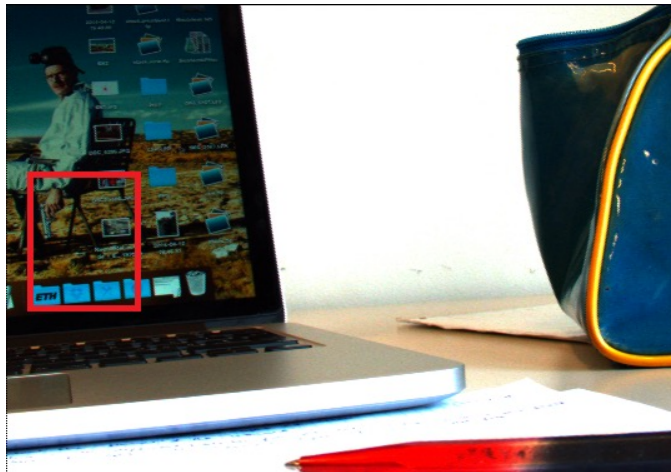
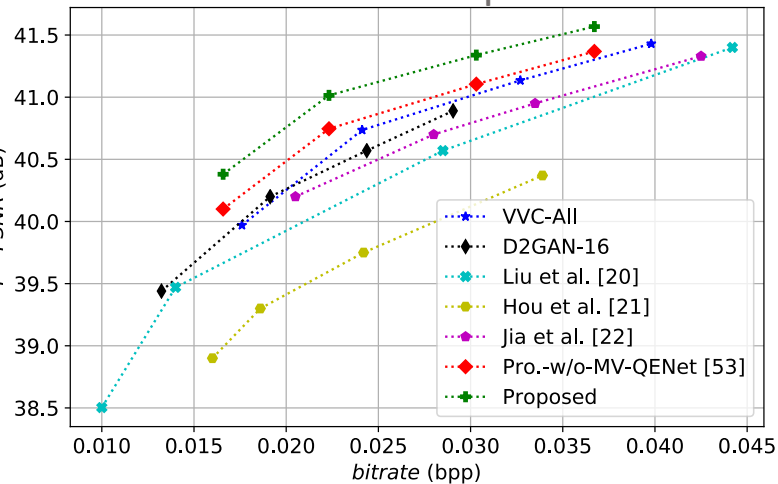
VVC-All  
y-psnr: 39.86



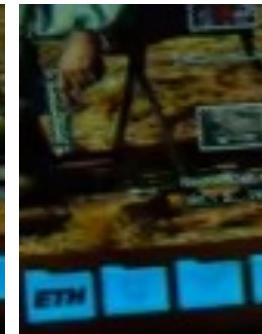
Our w/o QE  
y-psnr: 40.08

@0.032 bpp

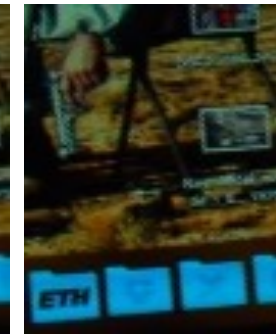
Desktop



[Liu et al.]  
y-psnr: 40.12



VVC-All  
y-psnr: 40.36



Our w/o QE  
y-psnr: 40.65

@0.021 bpp

□ Complexity analysis : run time on CPU (Inter i9-7900X 3.3GHz) & GPU (NVIDIA TITAN XP)

|                           | Encoder run time (second) |                   |                   |               |           |
|---------------------------|---------------------------|-------------------|-------------------|---------------|-----------|
|                           | VVC-All                   | [Jia et al. 2018] | [Hou et al. 2019] | Ours          |           |
| QP                        | CPU                       | GPU               | CPU               | CPU           | GPU       |
| 22                        | <b>259</b>                | 450               | 6028              | 559           | 449       |
| 26                        | <b>152</b>                | 350               | 6028              | 452           | 342       |
| 32                        | <b>101</b>                | 220               | 6028              | 401           | 291       |
| 37                        | <b>66</b>                 | 142               | 6028              | 366           | 256       |
| <b>Average</b>            | <b>145</b>                | 291               | 6028              | 445           | 335       |
| Decoder run time (second) |                           |                   |                   |               |           |
| <b>Average</b>            | <b>4</b>                  | 53                | 583               | 124 to<br>333 | 94 to 285 |

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## □ Contributions

- New **D2GAN** model for **LF** image **Synthesis**
- Efficient coding solution outperforming the state-of-the-art learning based coding approach
- **Open Questions**
  - **Encode or Synthesize ?**
  - **What about the Depth Information ?**
  - **Subjective Evaluation ?**

<https://naderbakir79.github.io/LFD2GAN.html>



## Thank you for your attention



## □ References

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