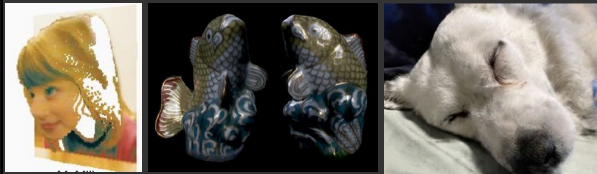


Image-Based Rendering

CSE 274, Lecture 8: Deep Learning for IBR

Ravi Ramamoorthi

<http://www.cs.ucsd.edu/~ravir>



1

To Do

2

Motivation

- Some of first Deep Learning IBR papers
 - Now widespread in view synthesis algorithms
 - Will talk about NeRFs next week
 - Include as background other work like MPIs
- 3 early works from my group (postdoc Nima Kalantari LF cameras, Local Light Field Fusion)
- Have seen parts before but this delves into detail

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Utilizing Physics in Deep Learning for Graphics



Nima Khademi Kalantari

University of California, San Diego

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Deep learning

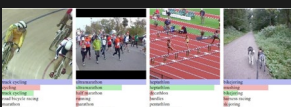
- Significant interest in deep learning
- Successfully applied to analysis applications



Image Classification
[Krizhevsky et al. 2012]



Object Detection
[Ren et al. 2015]



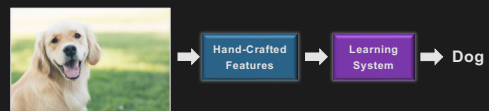
Video Classification
[Karpathy et al. 2014]



Image Captioning
[Karpathy and Fei-Fei 2015]

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Analysis applications



Traditional Methods



Deep Learning Methods

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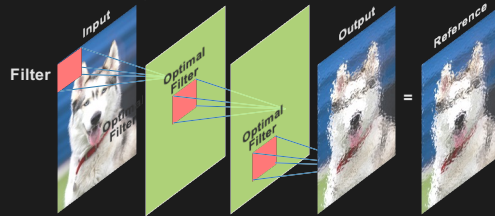
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Convolutional neural network (CNN)

- Efficient (can be implemented on GPUs)
- Model the process systematically
- Far less progress for synthesis applications



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Synthesis applications

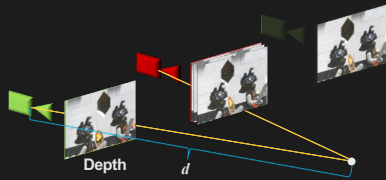
- Complex and structured

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View Synthesis

- Learning system needs to learn different steps during training



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Synthesis applications

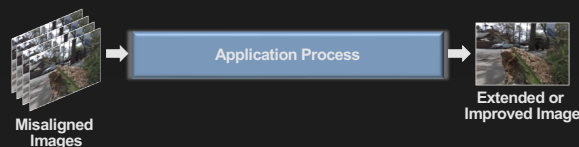
- Complex and structured
- Lack of large scale training data

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Proposed framework

- Incorporate physical insights into learning
- Observation: inputs are misaligned since they are from different views or times



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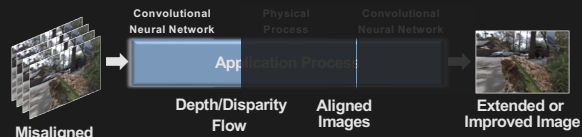
View synthesis



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Proposed framework

- Incorporate physical insights into learning
- Observation: inputs are misaligned since they are from different views or times
- Divide the process into smaller sub-problems



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View synthesis



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Our result



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Light fields



Refocusing

Viewpoint Change

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Consumer light field cameras



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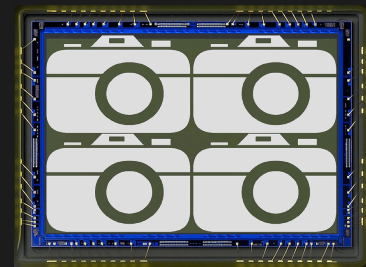
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Consumer light field cameras

- Sensor with fixed resolution



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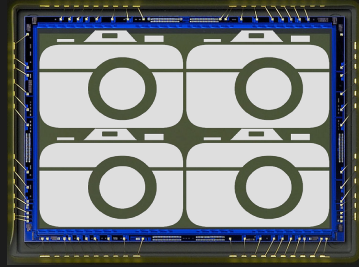
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Challenges

- Spatial / angular resolution trade-off

Low angular
High spatial



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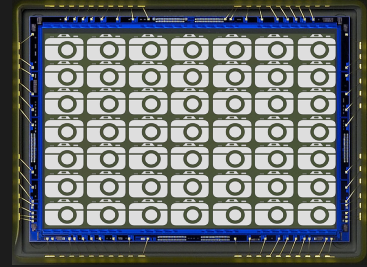
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Challenges

- Spatial / angular resolution trade-off

High angular
Low spatial



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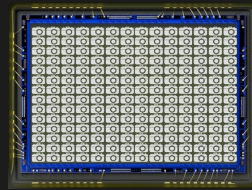
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Challenges

- Spatial / angular resolution trade-off
- 40 MP sensor resolution
- 14×14 angular resolution
- 0.2 MP spatial resolution



Lytro Illum



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Challenges

- Spatial / angular resolution trade-off
- Image resolution / frame rate trade-off
 - Fixed recording bandwidth



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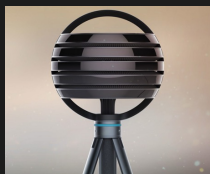
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Light field images and videos

- Applications in virtual and augmented reality
- Low cost cameras



Lytro Immerse



Samsung 360 Round 3

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Light field super-resolution

- Angular (SIGGRAPH Asia 2016)
- Temporal (SIGGRAPH 2017)

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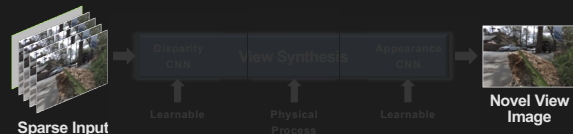
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Proposed method

- Use the general two stage framework



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Disparity estimator

- Goal:** estimate the disparity at every pixel of the novel view



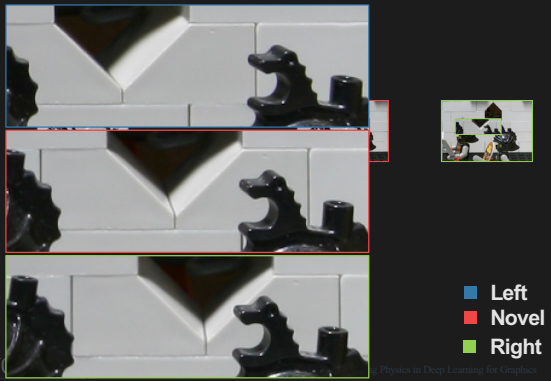
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Disparity estimator



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Disparity estimator

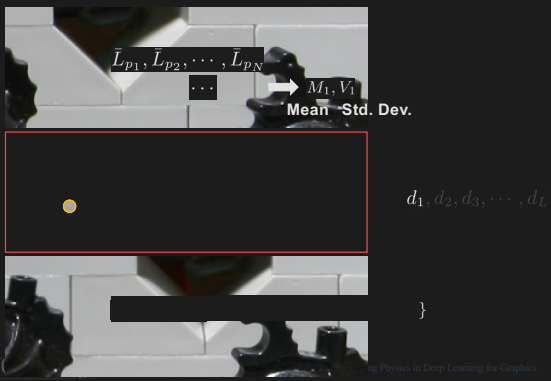


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Disparity estimator



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Disparity estimator



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Disparity estimator



$$d_1, d_2, d_3, \dots, d_L$$

$$K = \{M_1, V_1, M_2, V_2\}$$

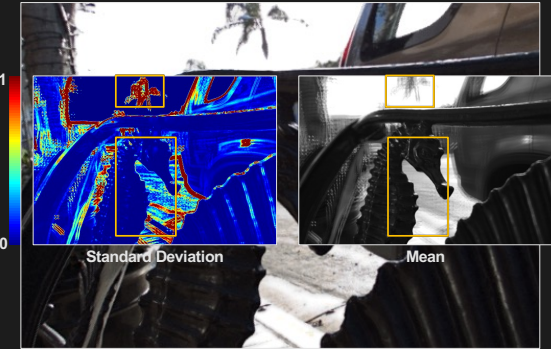
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Disparity estimator



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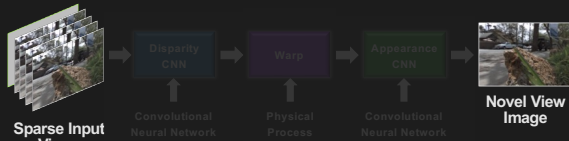
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Proposed method

$$L_q = f(L_{p_1}, \dots, L_{p_N}, q)$$

- Use the general two stage framework



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Appearance estimator

- **Goal:** estimate the final color from the warped images
- **Challenges**
 - Warped images contain invalid info around occlusion boundaries
 - Estimated disparity is not always accurate

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Appearance estimator features

- Warped images
- Disparity
- Position of novel view



$$H = \{\bar{L}_{p_1}, \dots, \bar{L}_{p_N}, D_q, q\}$$

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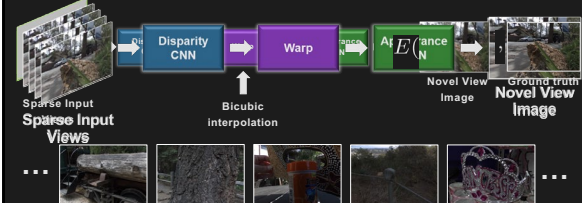
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Training

$$L_q = f(L_{p_1}, \dots, L_{p_N}, q)$$

- Use the general two stage framework
- Ground truth disparity maps are not required



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Dataset

- Captured data with a Lytro Illum camera
- Angular resolution of 8×8
- Training data consists of 100 light fields



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FLOWER (previous approach)



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Wang et al. [2015]

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FLOWER (ours)



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Ours

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FLOWER (ground truth)

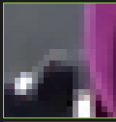


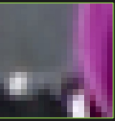
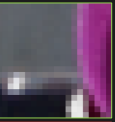
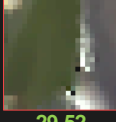

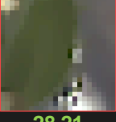
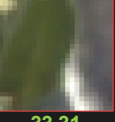
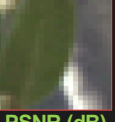


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Ground Truth

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FLOWER

Tao et al.	Wang et al.	Jeon et al.	Ours	GT
				
				
29.52	24.39	28.21	33.31	PSNR (dB)
0.941	0.910	0.934	0.969	SSIM

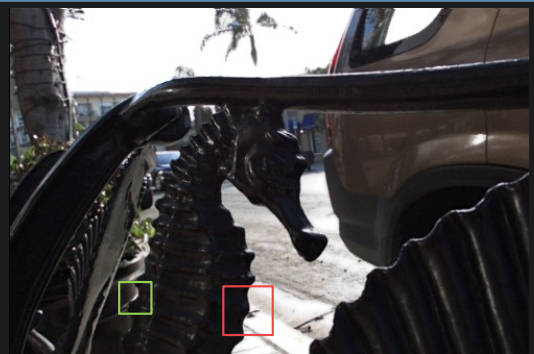
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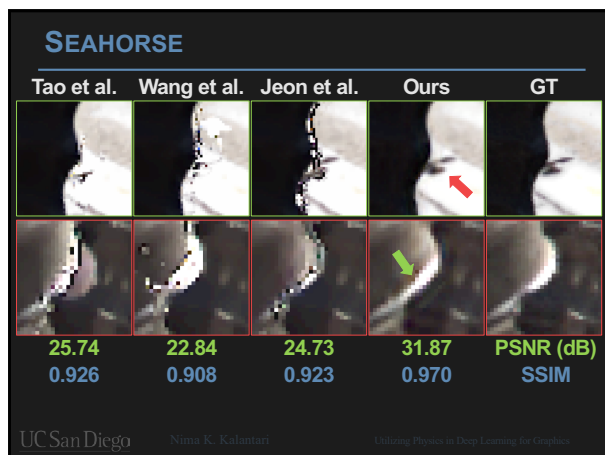
SEAHORSE (ours)



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Ours

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Impact

- Three orders of magnitude faster than Google's Deep Stereo [Flynn et al. 2016]
- Significant academic / industrial interest
- Has received funding from major companies and federal agencies
- Big step towards capturing high quality light fields with low cost cameras

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Light field super-resolution


- Angular (SIGGRAPH Asia 2016)
- Temporal (SIGGRAPH 2017)

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Motivation

- Lytro ILLUM: captures videos at 3 fps
- Direct temporal interpolation does not work

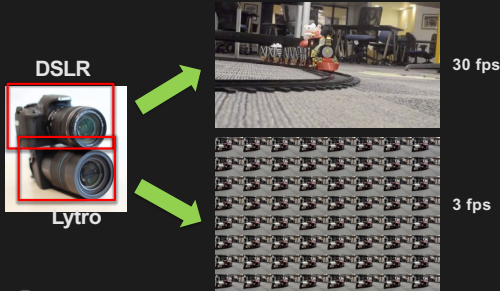


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Proposed System

- Capture temporal information using a regular video camera

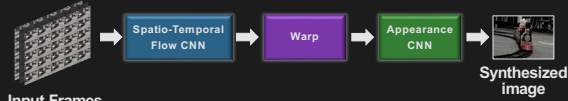


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Proposed method

- Use the general two stage framework



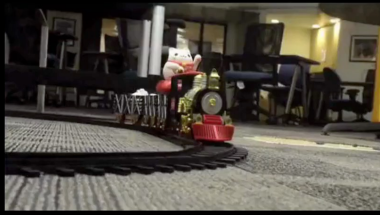
- Contributions
 - Hybrid capturing system
 - Spatio-Temporal CNNs (coarse-to-fine)
 - No need for ground truth flows

Details in the paper!

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Our Result



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Video refocusing



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Aperture changing



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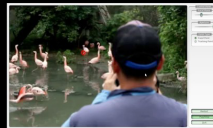
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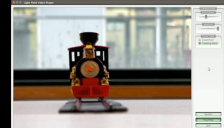
51

Light Field Video Applications

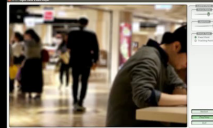
video refocusing



focus tracking



aperture changing

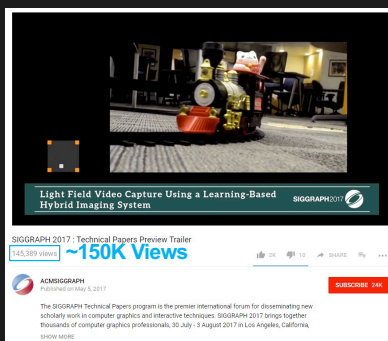


view changing



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SIGGRAPH technical paper trailer



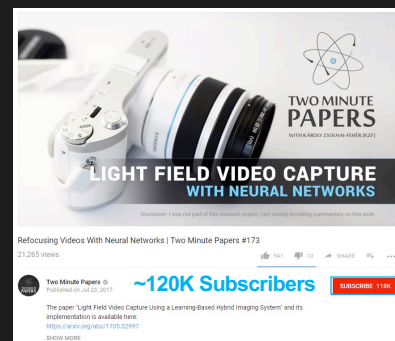
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Two Minute Papers



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