Image-Based Rendering

CSE 274, Lecture 8: Deep Learning for IBR

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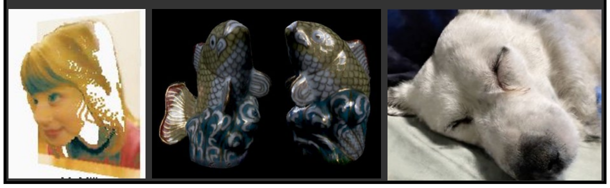
http://www.cs.ucsd.edu/~ravir



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To Do

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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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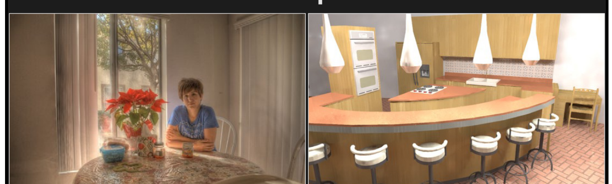
Utilizing Physics in Deep Learning for Graphics



Nima Khademi Kalantari

University of California, San Diego

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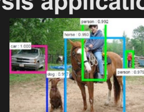
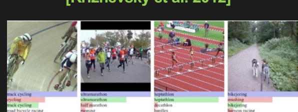
Deep learning

- 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]

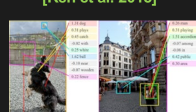


Image Captioning
[Karpathy and Fei-Fei 2015]

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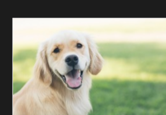
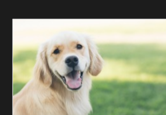
Analysis applications



→ Hand-Crafted Features → Learning System → Dog

Traditional Methods



→ Deep Neural Network → Dog

Deep Learning Methods

UC San Diego Nima K. Kalantari Utilizing Physics in Deep Learning for Graphics

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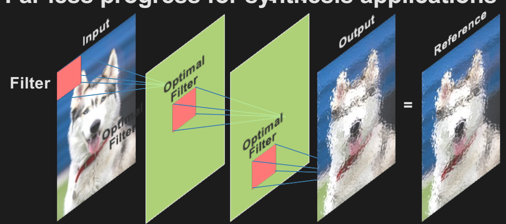
Convolutional neural network (CNN)

- 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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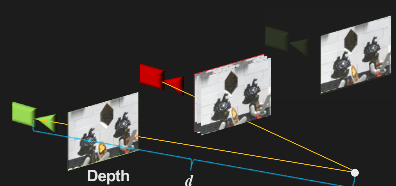
View Synthesis

- 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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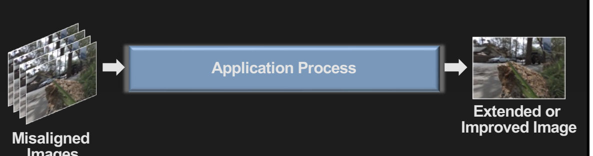
Proposed framework

- 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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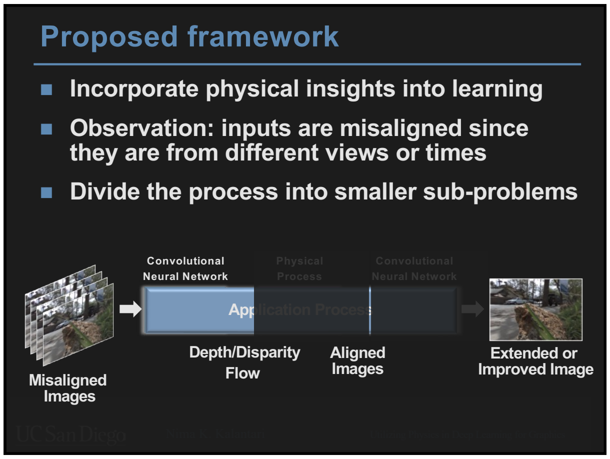

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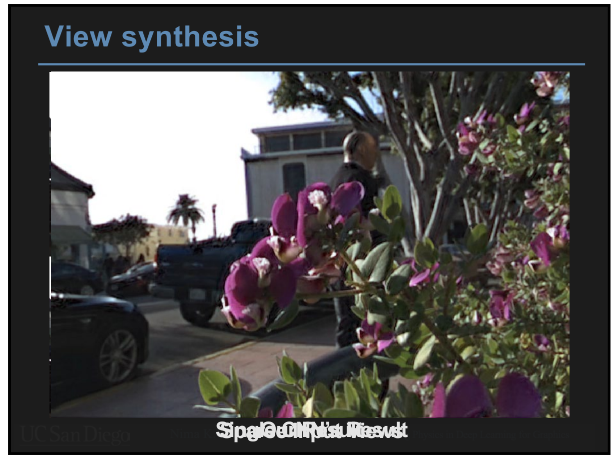

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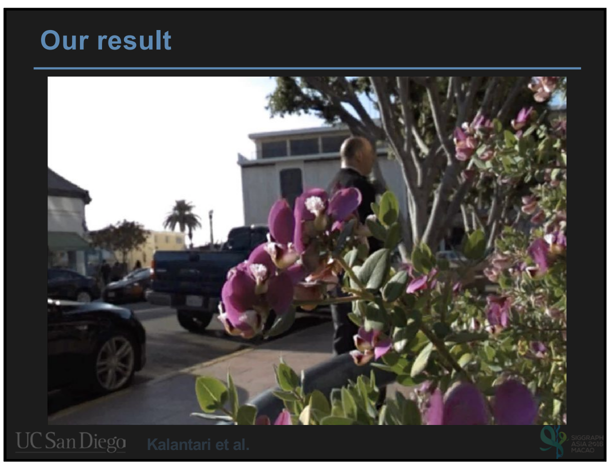

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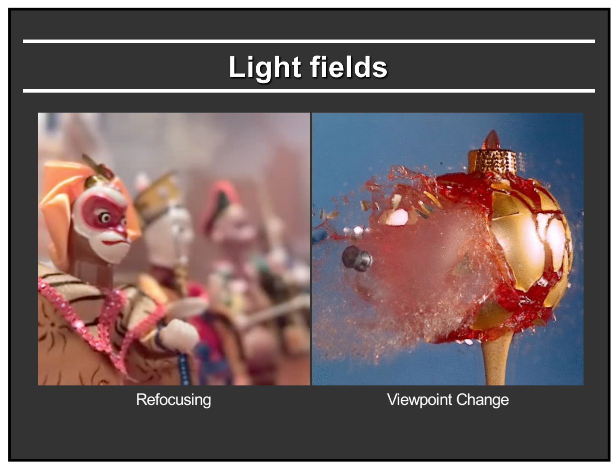

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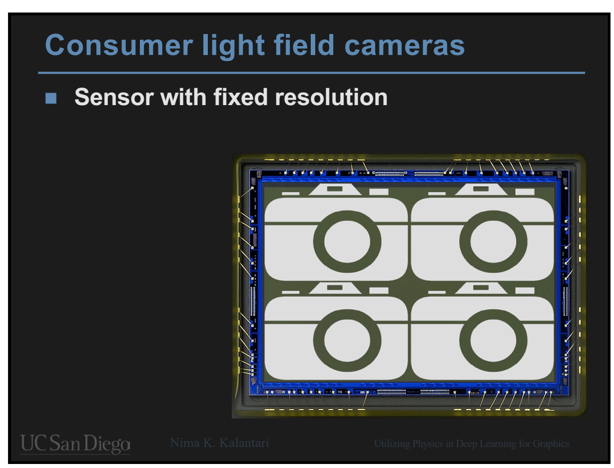

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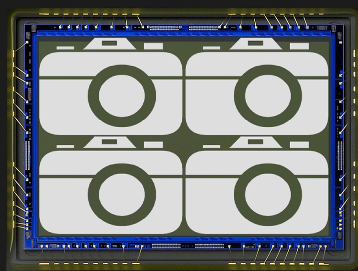
Challenges

- Spatial / angular resolution trade-off

Low angular
High spatial



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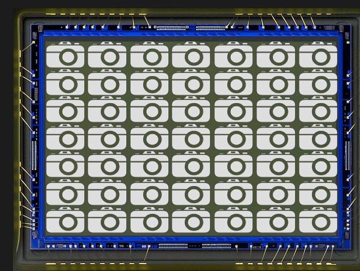
Challenges

- Spatial / angular resolution trade-off

High angular
Low spatial



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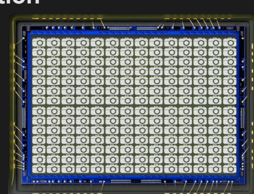
Challenges

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

Lytro Illum



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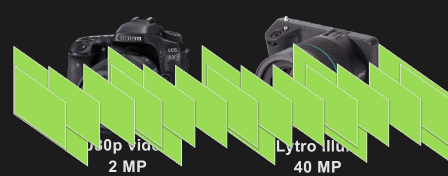
Challenges

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



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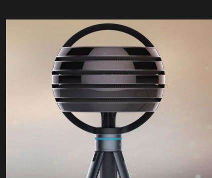
Light field images and videos

- Applications in virtual and augmented reality
- Low cost cameras



Lytro Immerge

Samsung 360 Round 3

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Light field super-resolution

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

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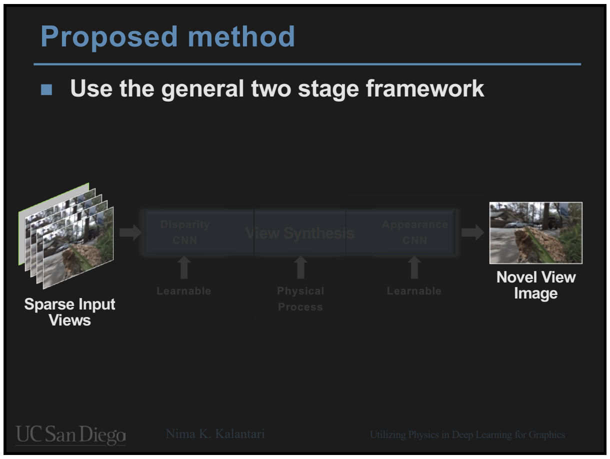

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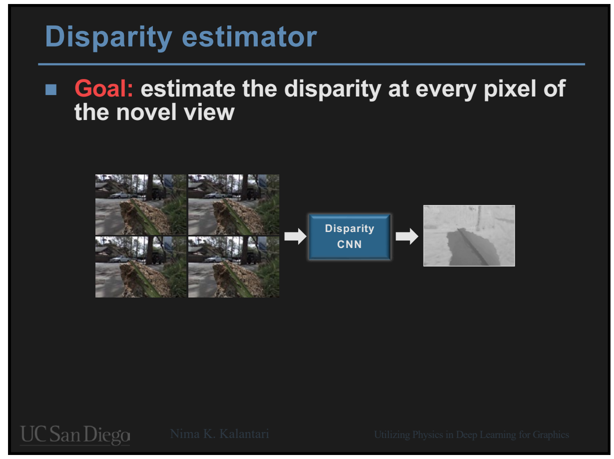

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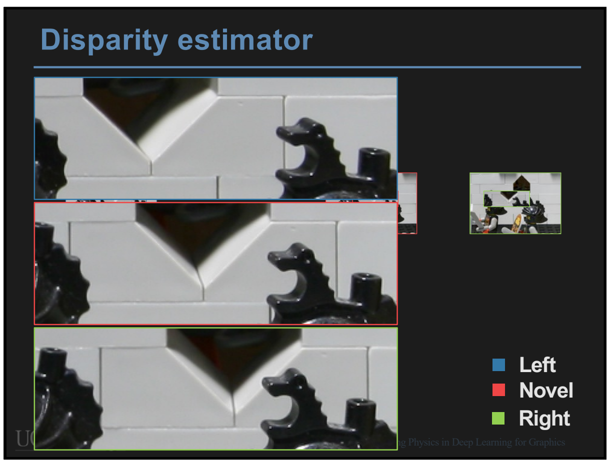

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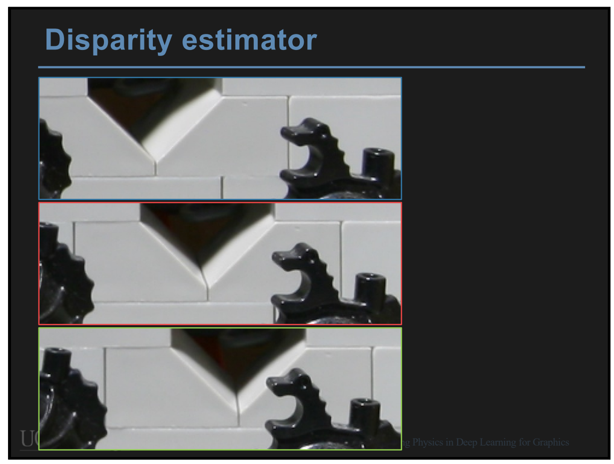

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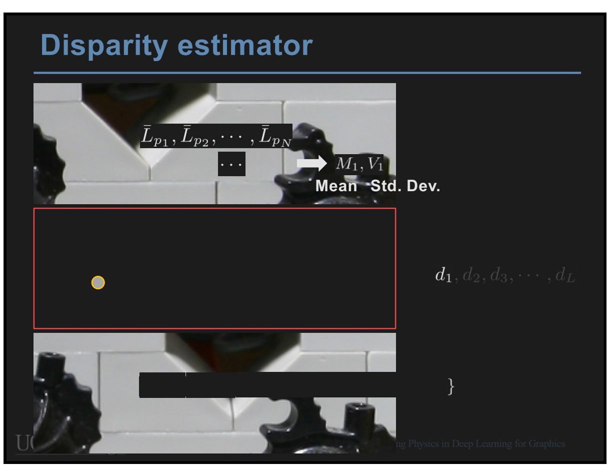

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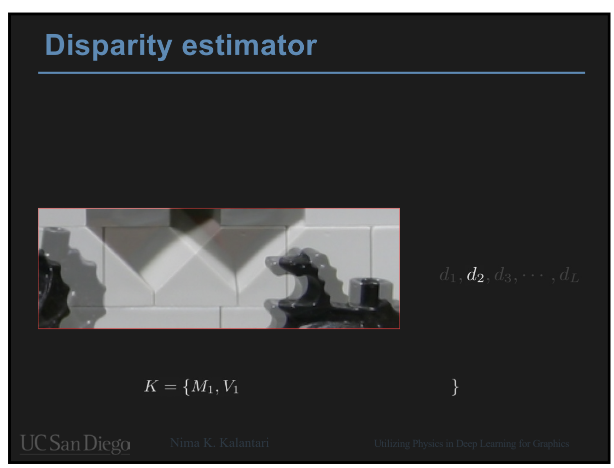

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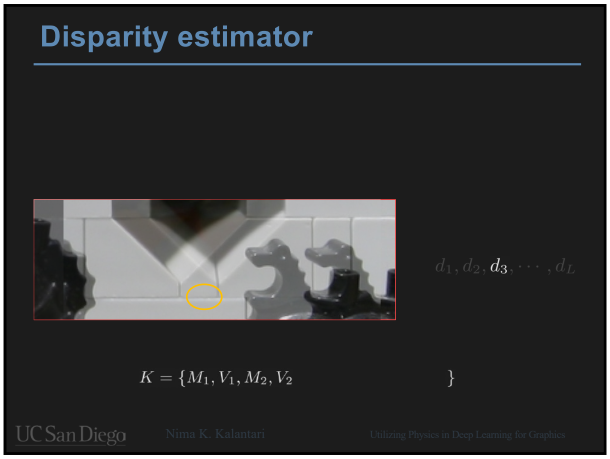

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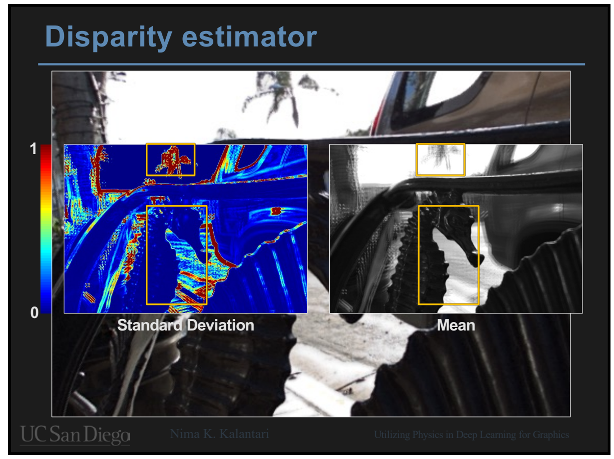

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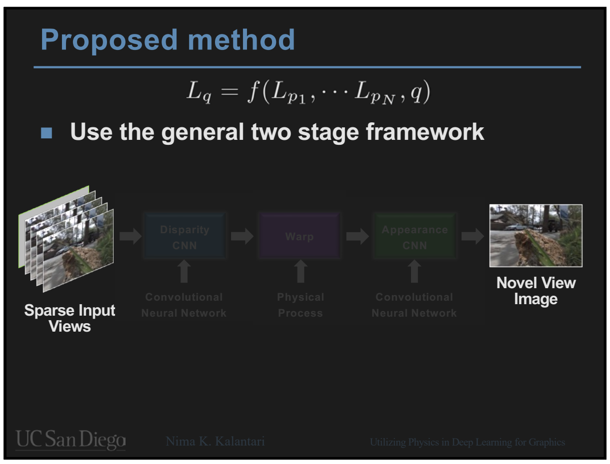

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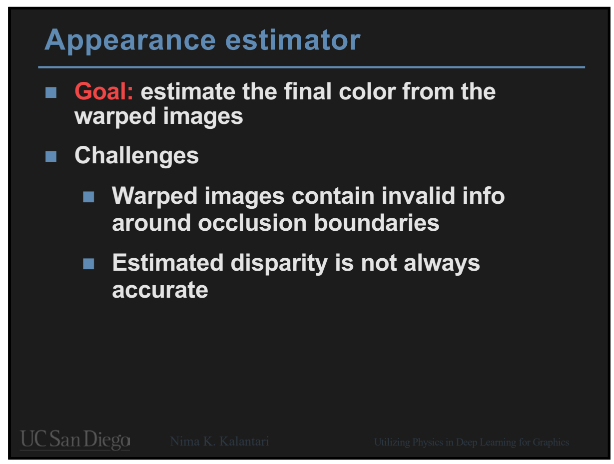

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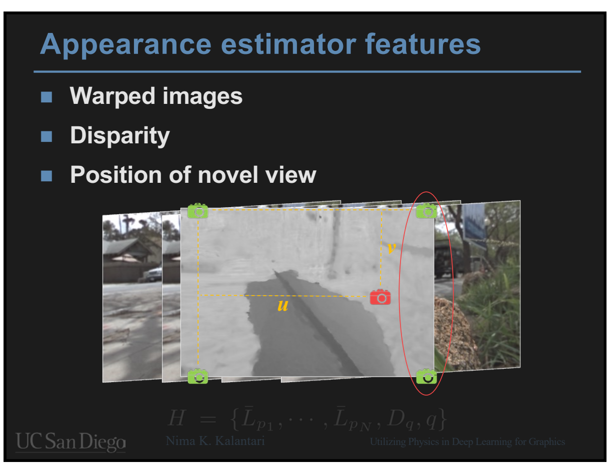

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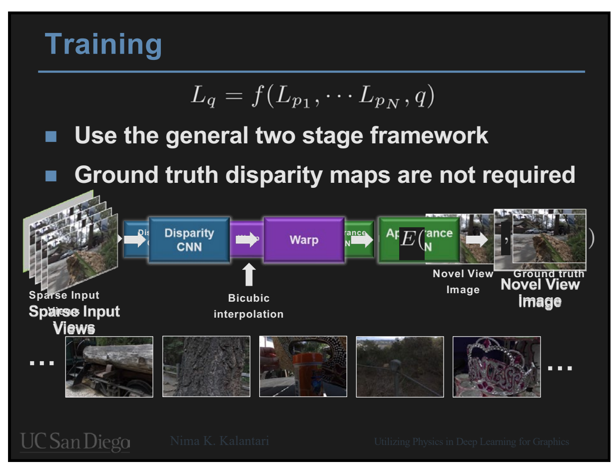

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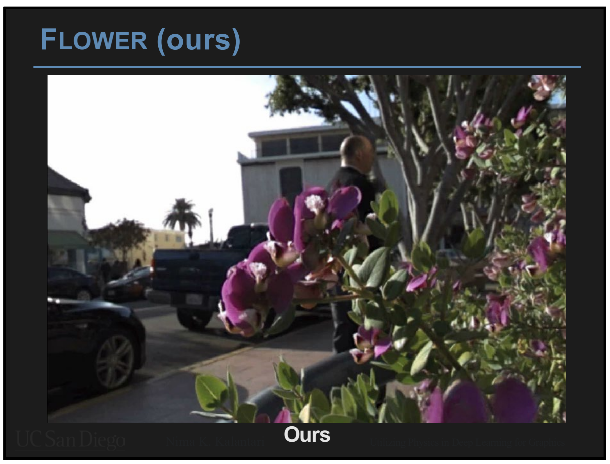

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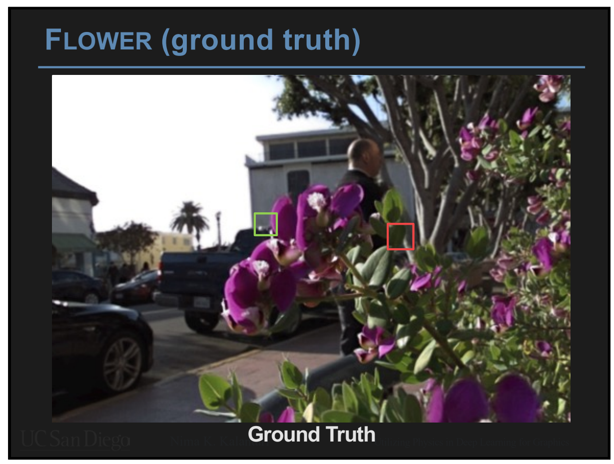

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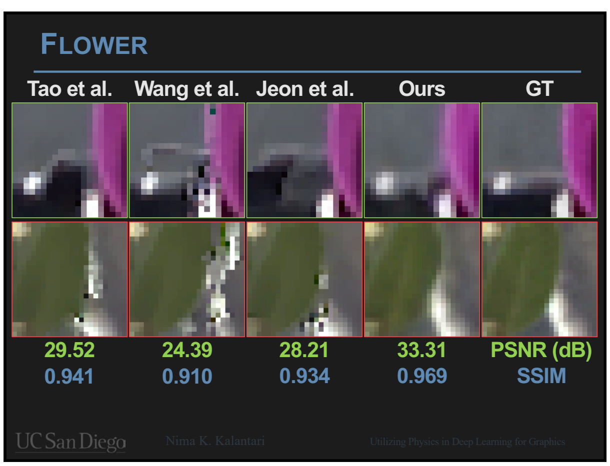

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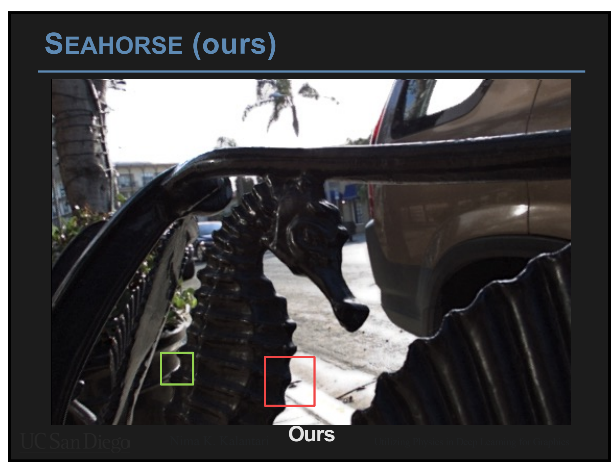

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SEAHORSE

Tao et al.	Wang et al.	Jeon et al.	Ours	GT
25.74	22.84	24.73	31.87	PSNR (dB)
0.926	0.908	0.923	0.970	SSIM

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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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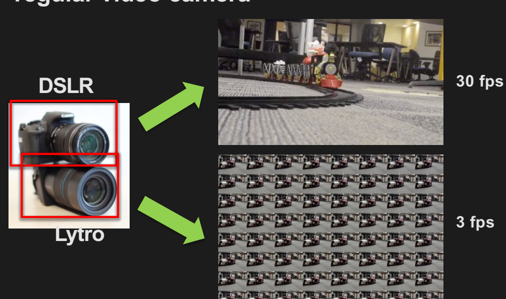
Proposed System

- Capture temporal information using a regular video camera



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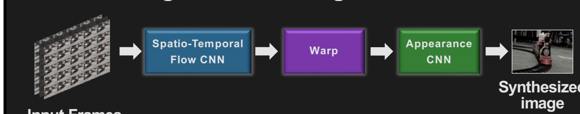
Proposed method

- 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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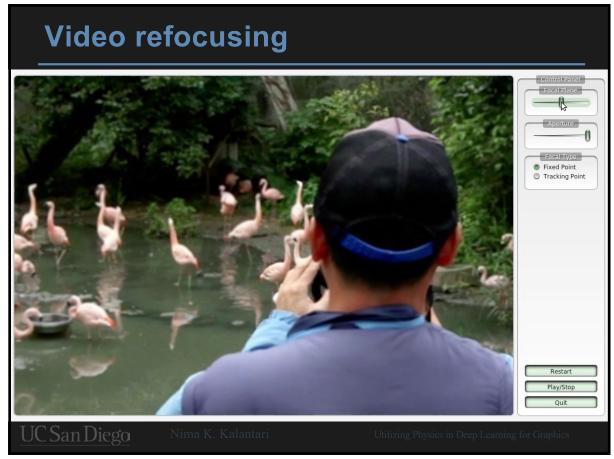

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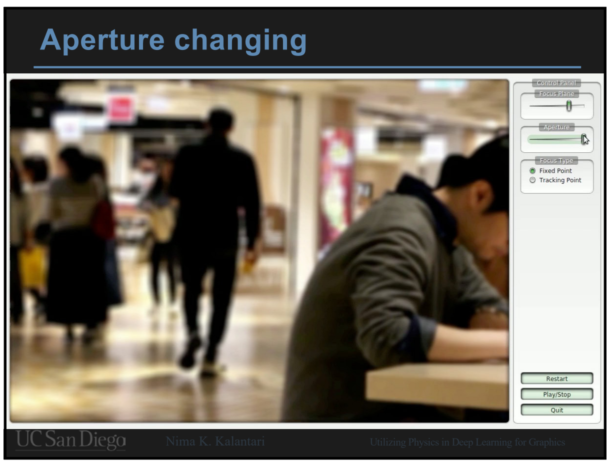

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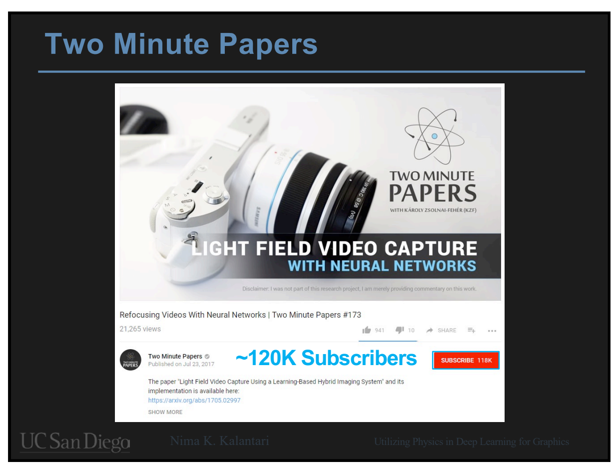

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