

Data-driven Hallucination of Different Times of Day from a Single Outdoor Photo

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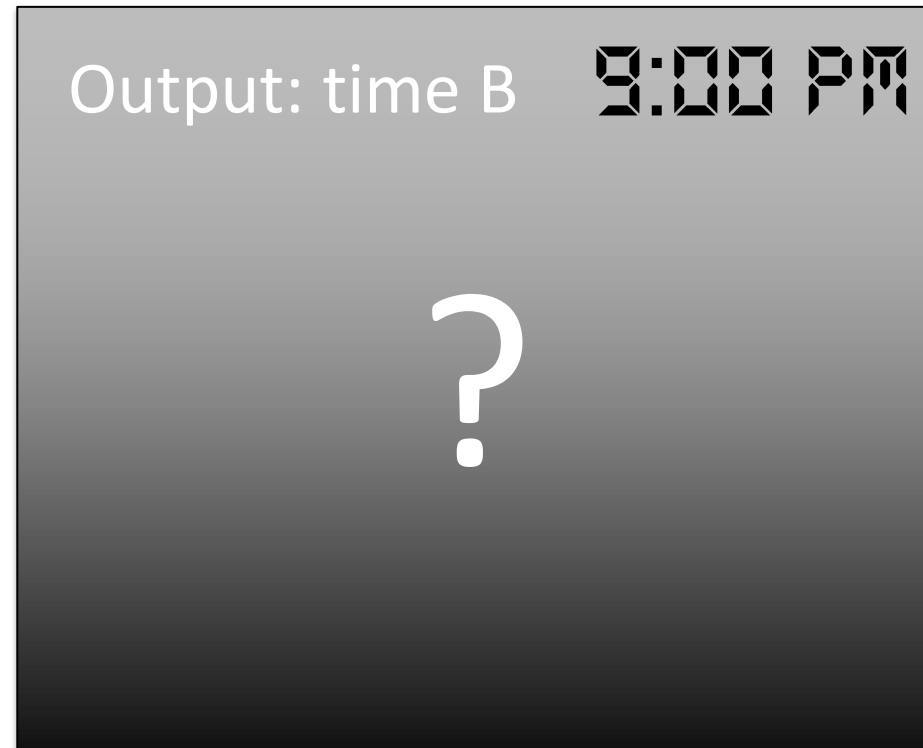


²Adobe



Hallucinating scene color variation over time

- Goal: use the photo at time A to predict the photo at time B.



Hallucinating scene color variation over time

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46 minutes too early [kenrockwell.com]



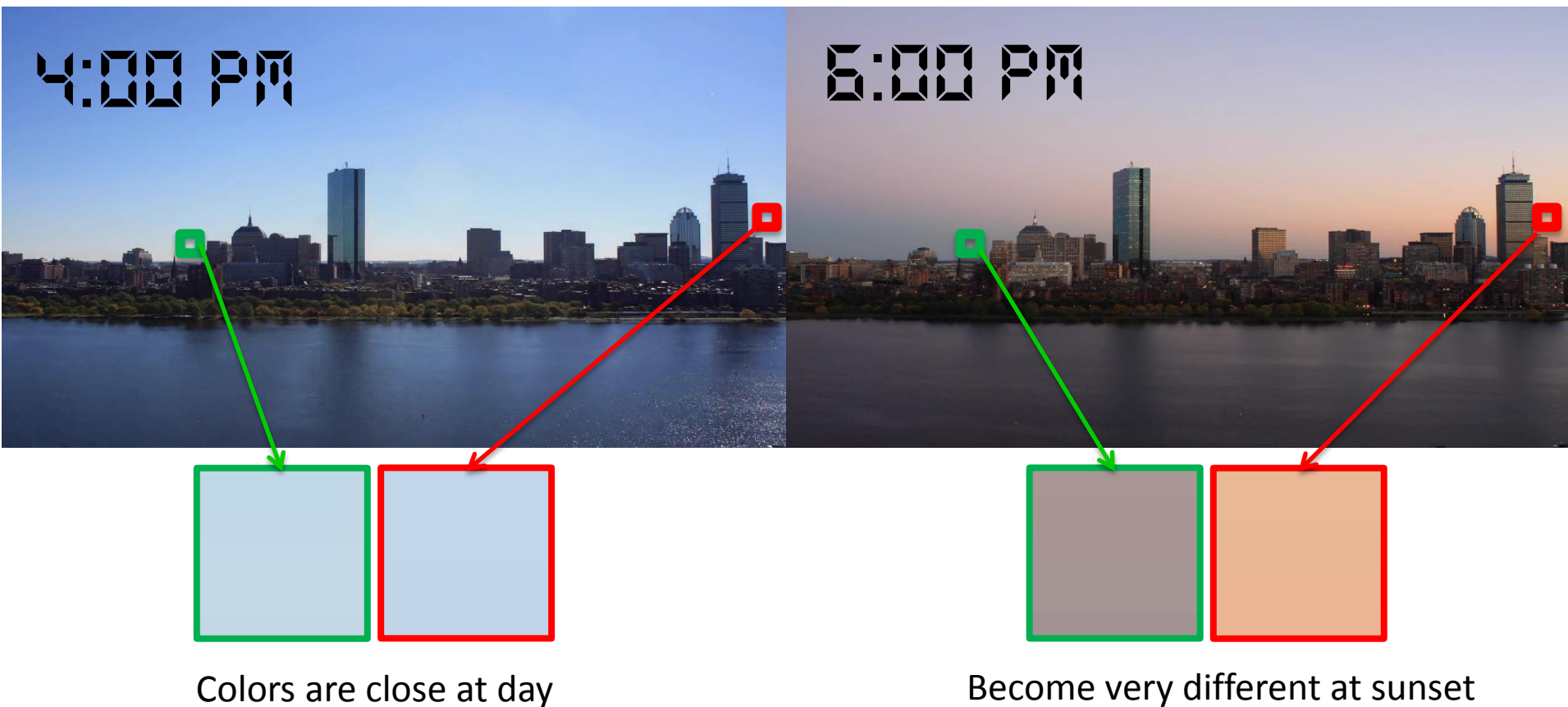
perfect [kenrockwell.com]



39 minutes too late [kenrockwell.com]

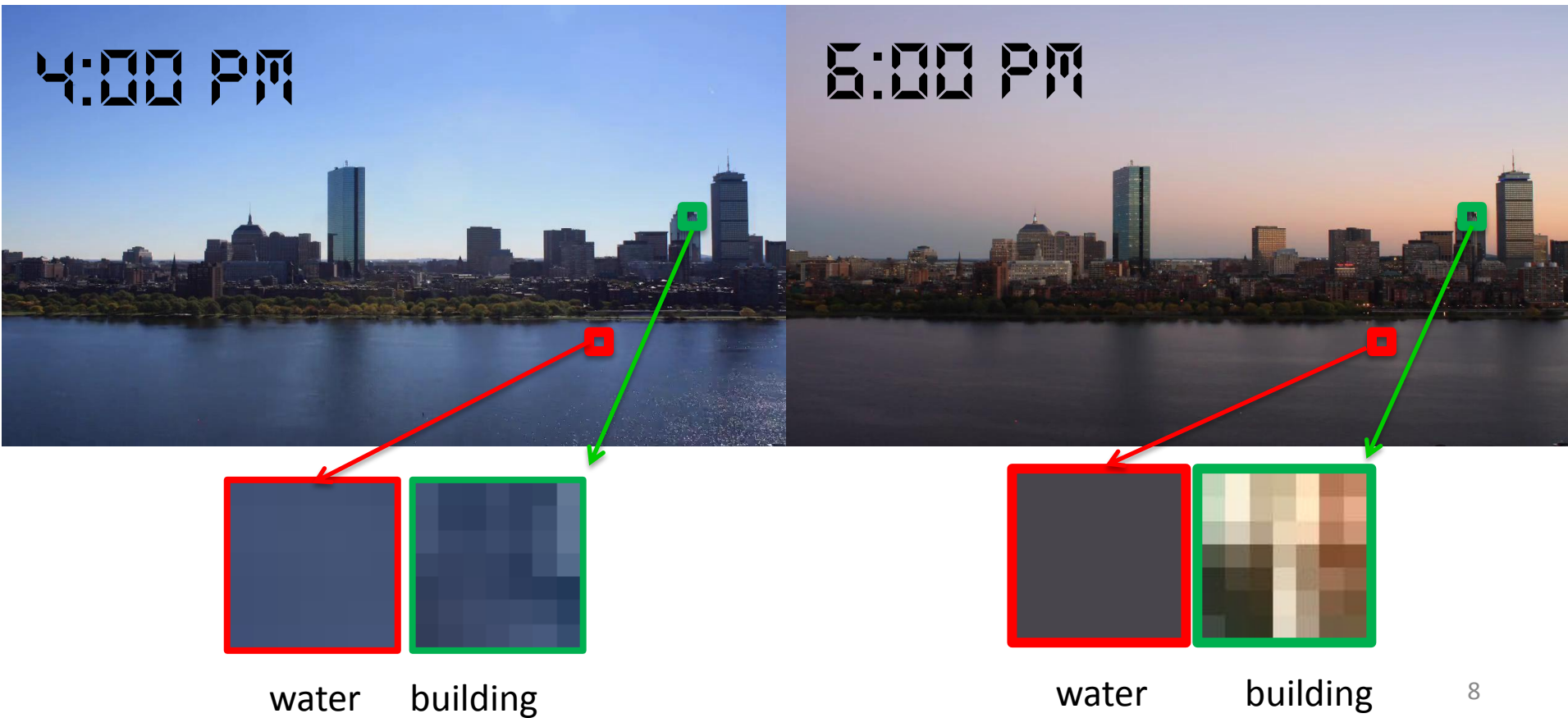
Hard problem

- The color change is spatially-variant!



Hard problem

- The color change depends on object
 - water and building become different color



Related work: global color transfer

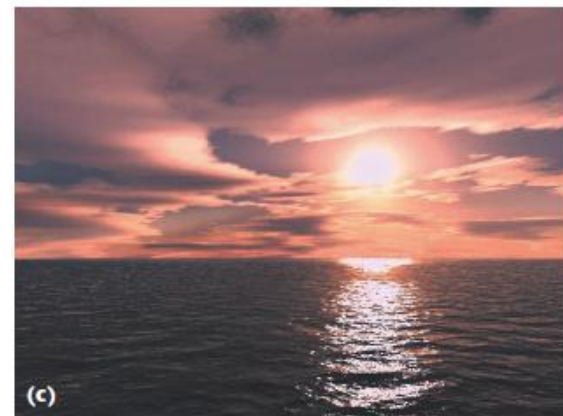
- Works on simple scenes [Reinhard et al, 2005] [Pouli and Reinhard, 2011] [Pitie et al. 2005]
- But complex scenes require spatially-variant color transfer



Input at daytime



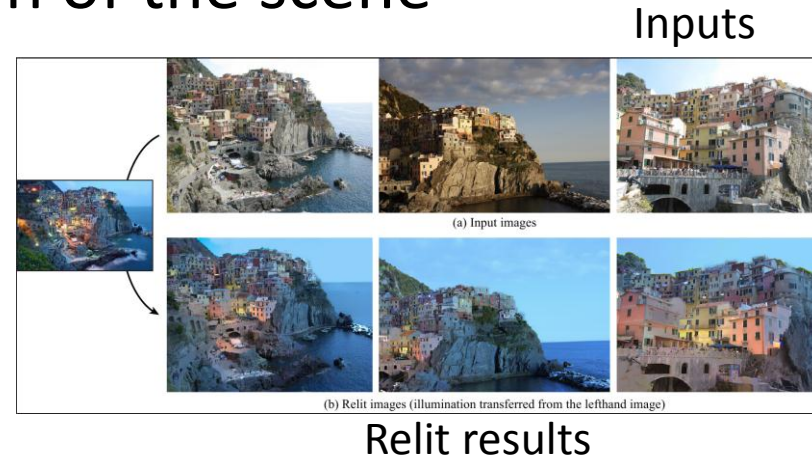
Example at sunset



Output at sunset

Related work: image relighting

- Intrinsic images [Laffont et al., 2012]
 - need image collection of the scene



- Deep Photo [Kopf et al., 2009]
 - need 3D information



- We want a general machinery,
not rely on data for specific input image

Related work: analyzing time-lapse sequence

- Produce good results, but need manually modeling the scene [Lalonde et al, 2009]



Input at daytime



Time A



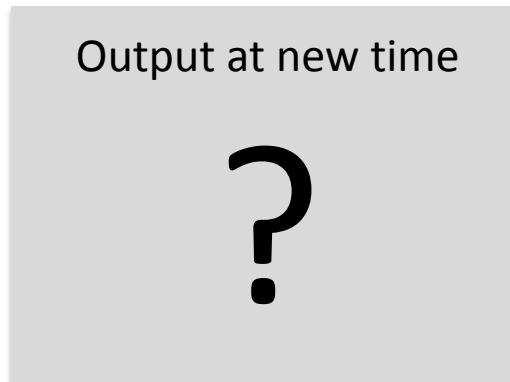
Time B



Time C

Problem statement

- Input: single photo + target time of day
- Output: the same scene as if it was taken at the target time of day



- Requirement: fully automatic, no user input

Key idea: using time-lapse videos



Containing videos

- 500 videos at various scenes
- Labeled with time of day

Overview

Input



Target time: 9pm

Overview

1. Match input to video from database

Input



Target time: 9pm

Matched time-lapse video

Matched frame 5:00 PM



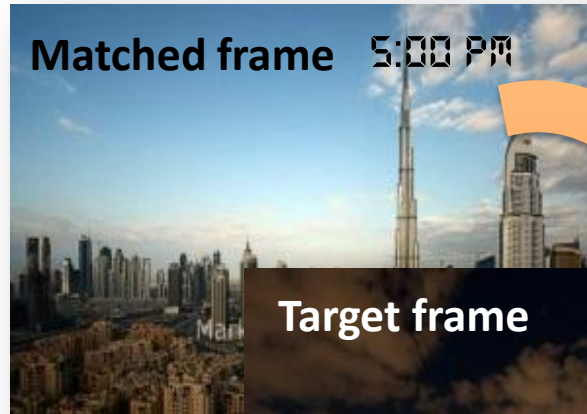
Overview

1. Match input to video from database



Target time: 9pm

Matched time-lapse video



Overview

1. Match input to video from database
2. Transfer color change



Target time: 9pm

Matched time-lapse video

Match frame 5:00 PM

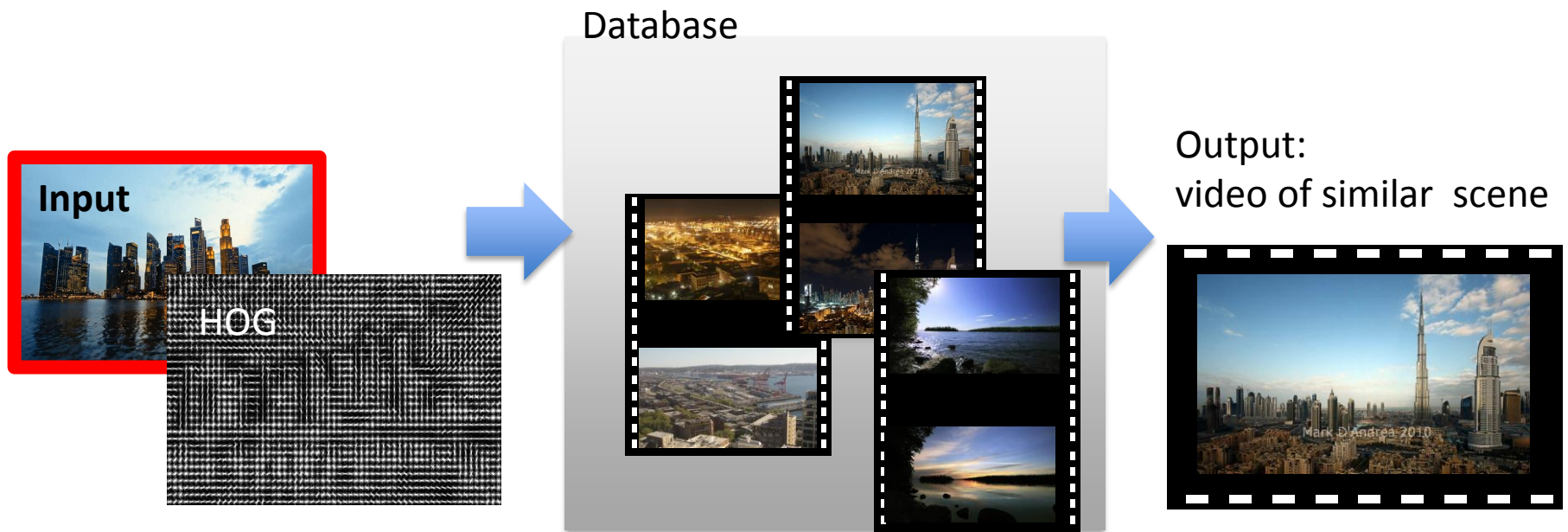
Transfer color change

Target frame 9:00 PM

Output

Matching step 1: video level

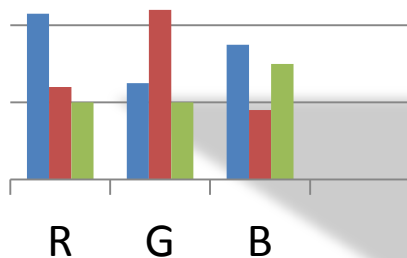
- Video retrieval with off-the shelf scene matching technique [Xiao et al, 2010]



Matching step 2: frame level

- Select the best match frame by color histogram metric

Input

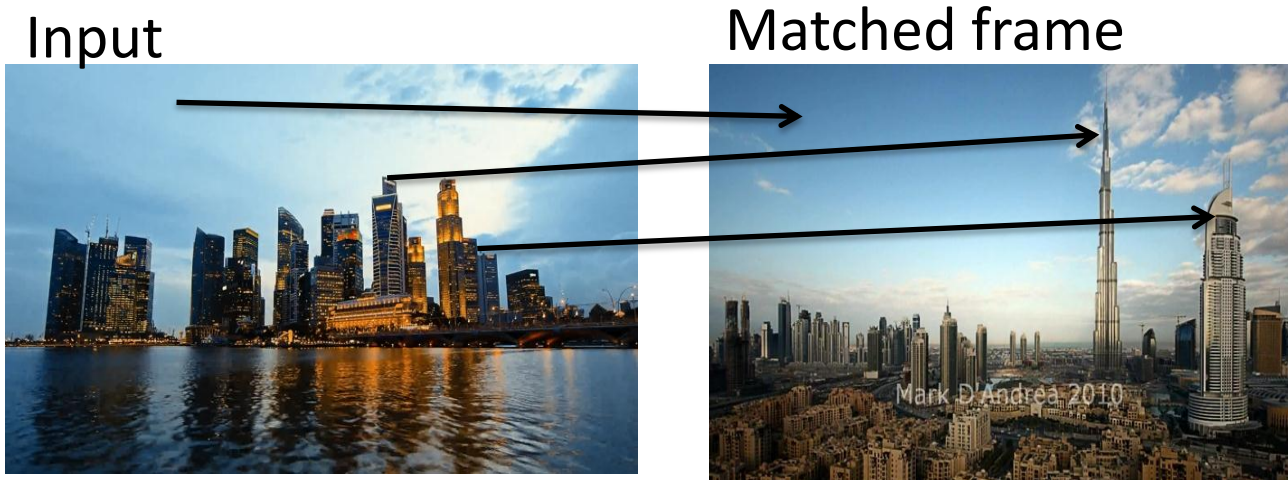


Matched frame



Matching step 3: pixel level

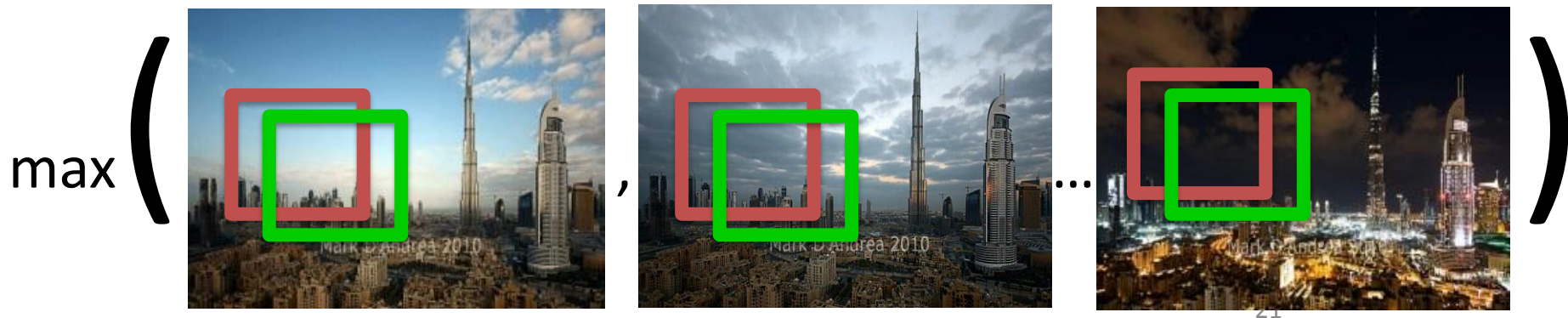
- Goal: respect scene semantic
 - E.g., sky to sky, building to building



- Dense correspondence using Markov random field

Markov Random Field for dense matching

- Data term: standard L2 norm
- Regularization term: aggregate over the entire sequence, not just the matched frame
 - Consistency over all time of day



Validating the matching

- Warp the matched frame to input using the dense correspondence



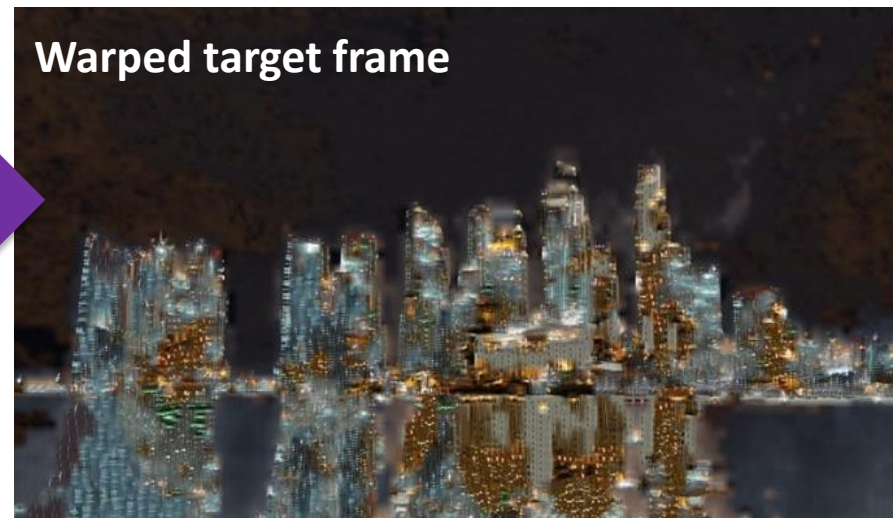
warp



Naïve transfer:

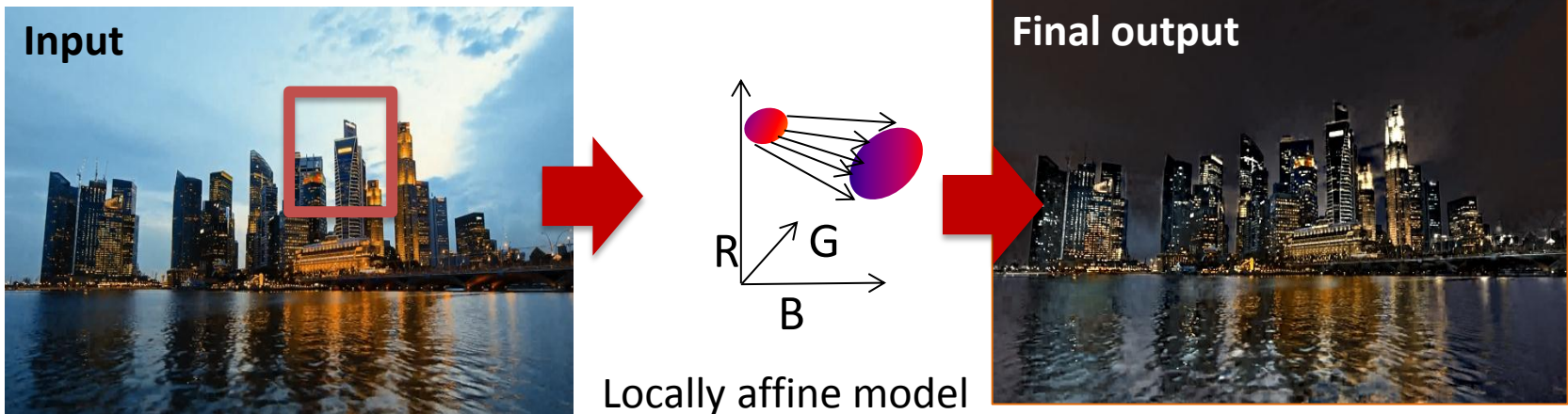
warp the target frame to the input

- Using the same correspondence
- The texture in the warped image is wrong
- Actually, the input already told us the texture.



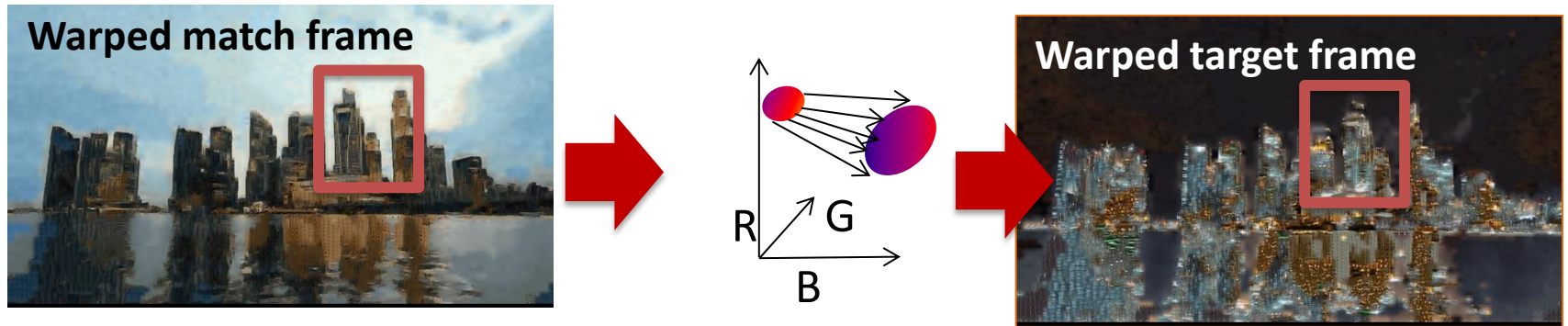
Our approach: locally affine color transfer

- *Local* to handle complex scenes
- *Affine* color transfer in each patch
 - preserve the structure of the input
 - match ground truth data; see paper.



Locally affine model explains the color change of time-lapse data

- In particular, explain matched frame and target frame



Locally affine model

The transfer needs to be locally affine everywhere

- The patches are overlapping, so we cannot estimate the affine model independently on each patch

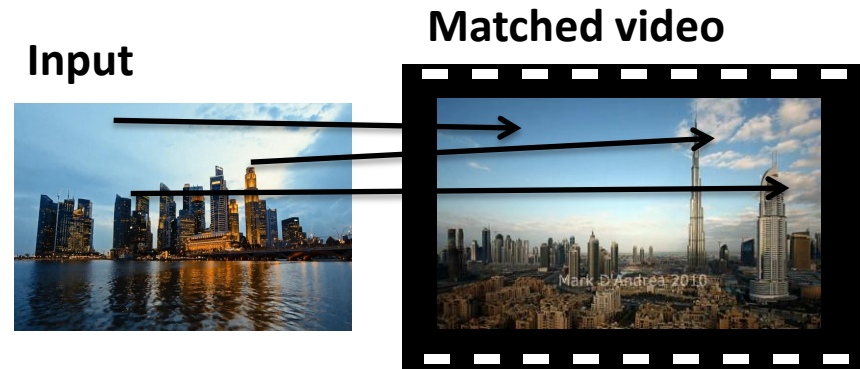
Color transfer as an optimization

- We are looking for color remapping function
 - Objective #1: explain time-lapse data
 - Objective #2: locally affine everywhere
- We design a least-squares energy
 - Sparse linear system
 - Formula and detailed analysis in the paper

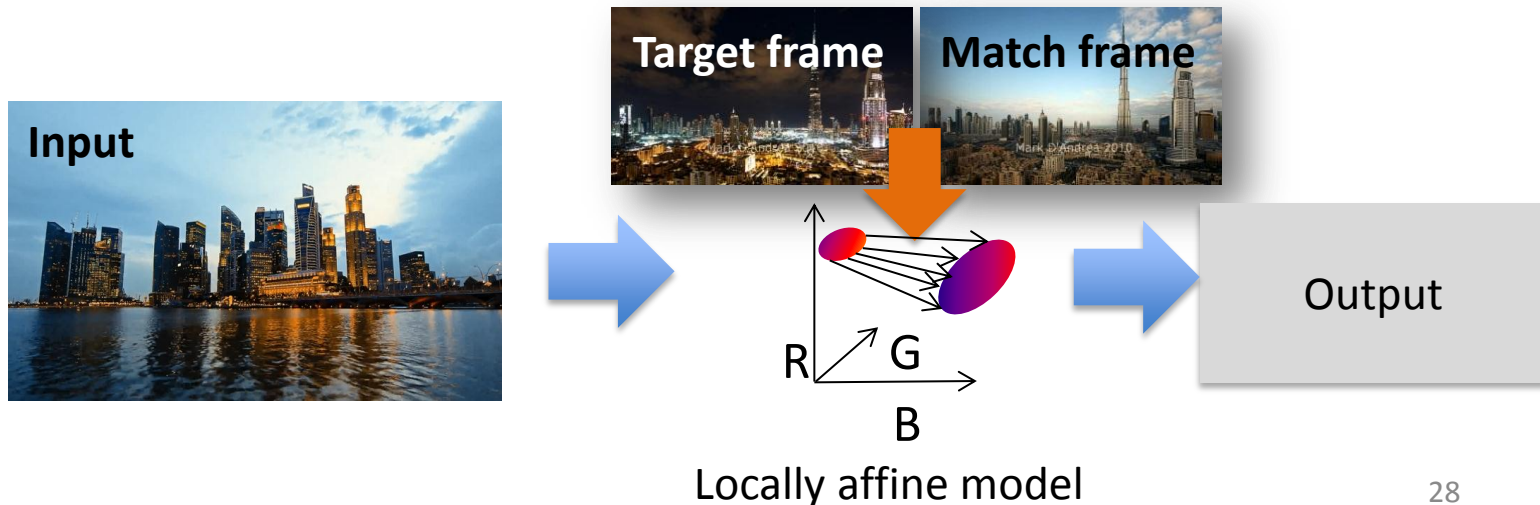
Recap

1. Match input to video

- i. scene matching
- ii. frame matching
- iii. dense matching



2. Locally affine color transfer



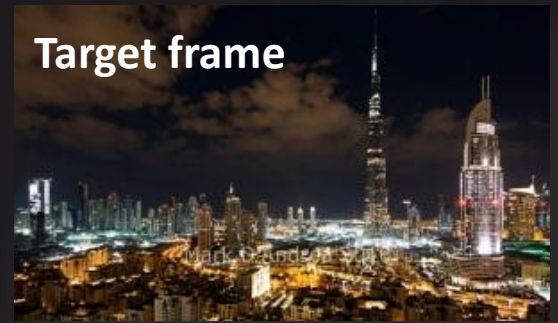
Input at sunset



Input at sunset



Our result at night



Results

- Same input for four different times of day

Input



Day



Before sunset (golden hour)

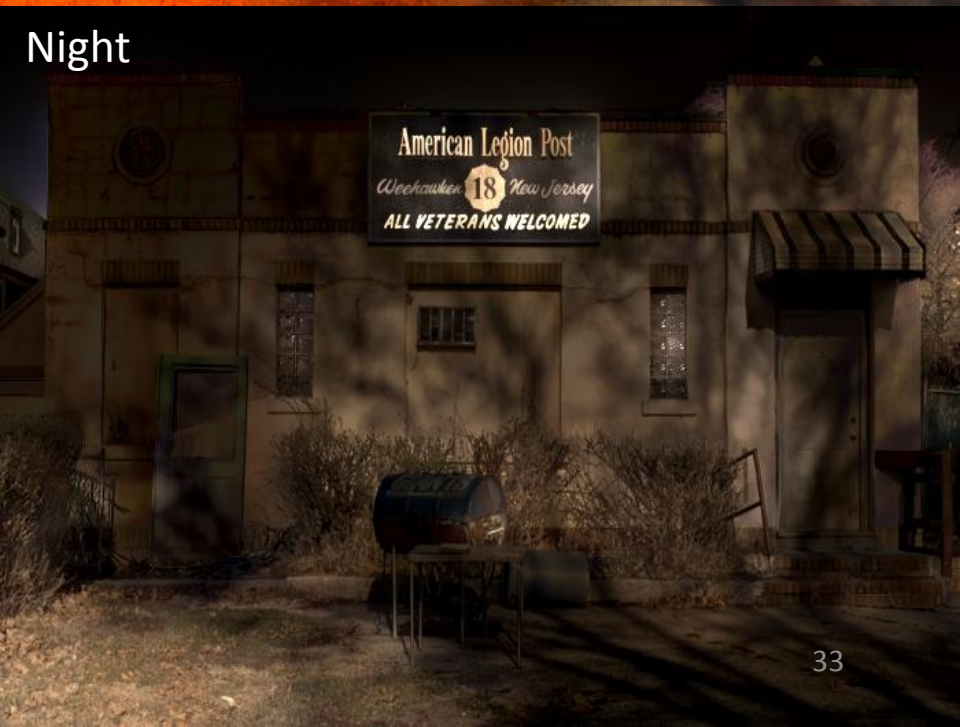


After sunset (blue hour)



Night



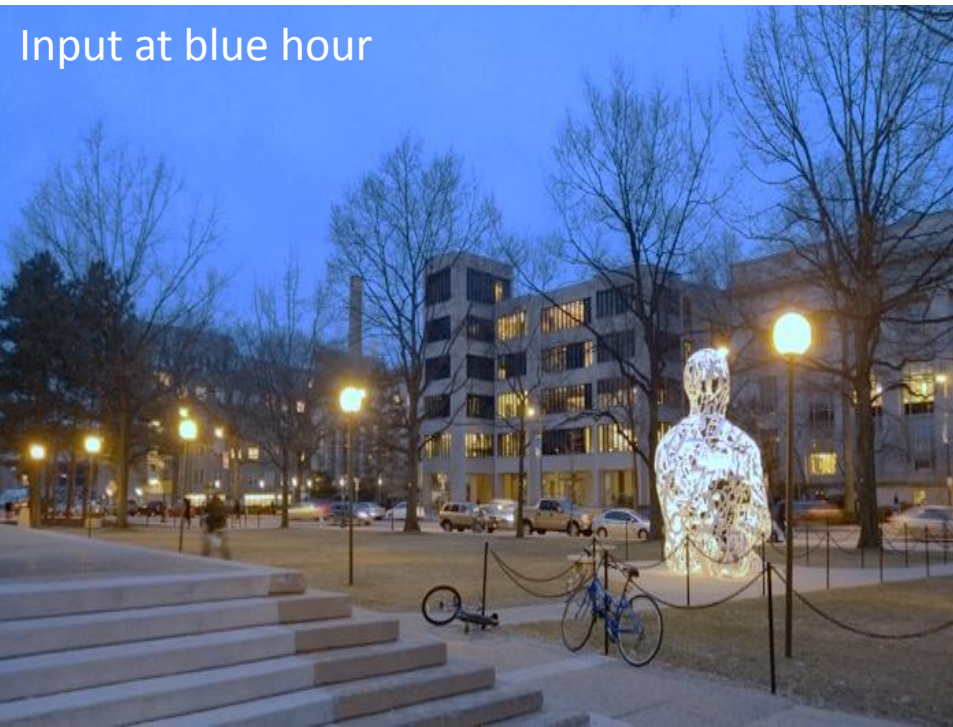


Ground truth validation

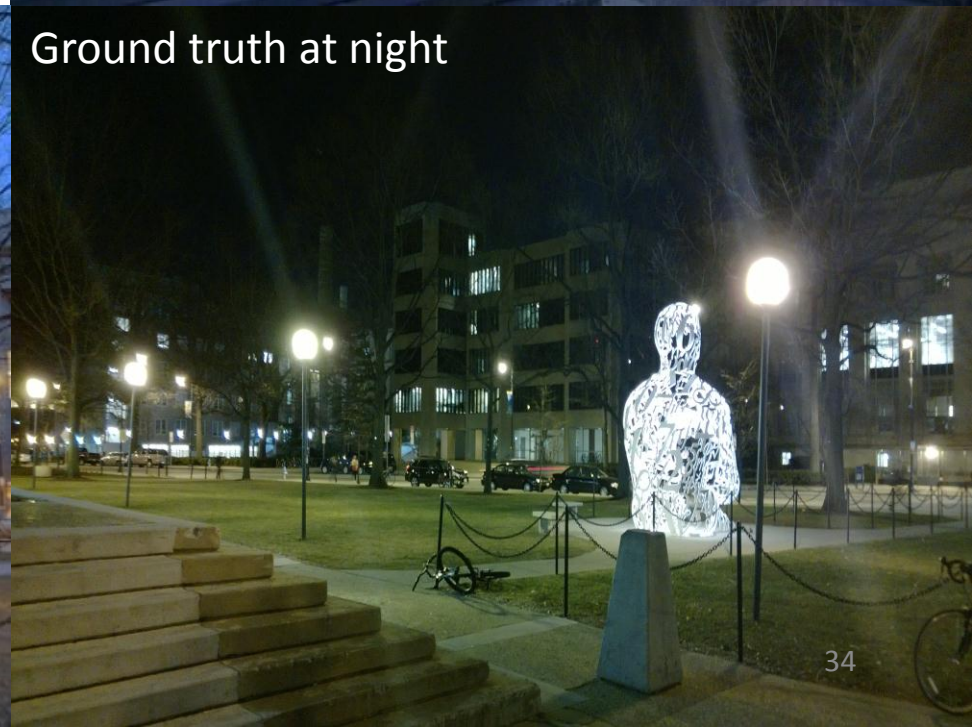
Our result at night



Input at blue hour



Ground truth at night

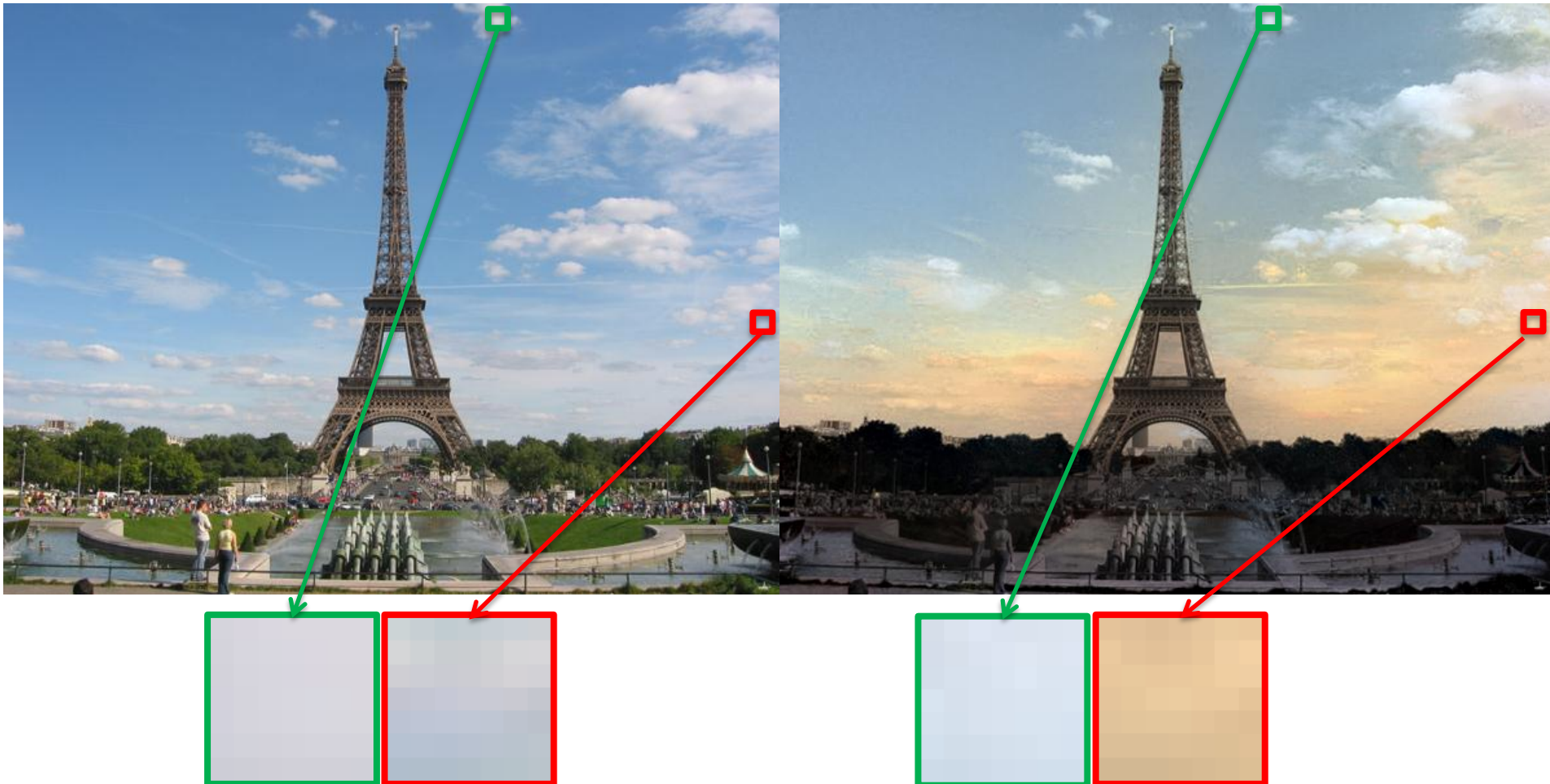


Our transfer is spatially-variant

- Our transfer is local.

Input at day

Output at golden hour



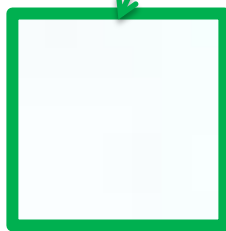
Our transfer is object-dependent

- We respect semantic in the scene.

Input at day



building

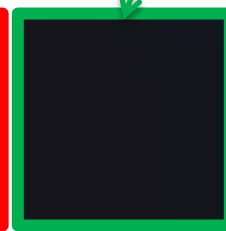


sky

Output at night



building



sky

Run-time Performance

- Image size: 700-pixels width.
- Matching takes 25 seconds
 - 2 seconds for scene matching.
 - 23 seconds for dense correspondence
- Locally affine transfer takes 32 seconds.
- Implemented with unoptimized Matlab

Various input image types: cloudy

Cloudy input



Output at after sunset

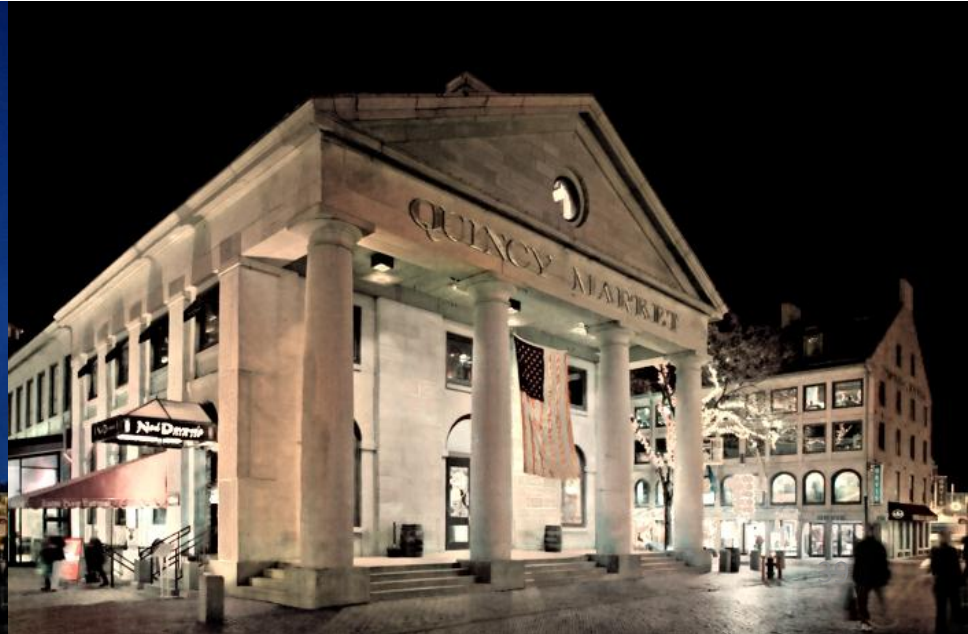


Various input image types: after sunset

Input at after sunset



Output at night



Results for different input scenes: mountain

Input at day



Output at blue hour



Results for different input scenes: lake

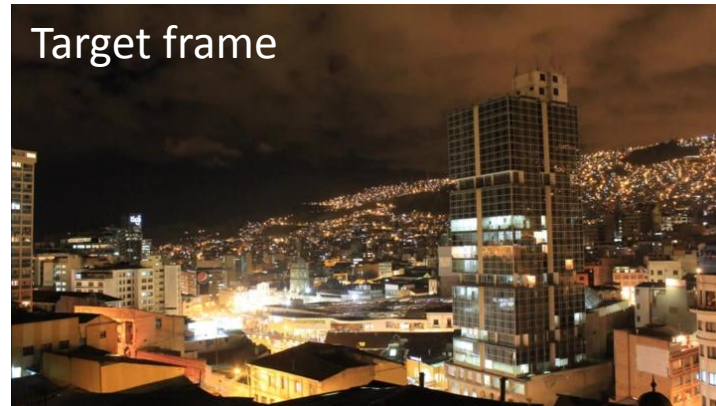
Input at day



Output at night



Comparison with other methods: translate to night



[Pitié et al. 2005]



[Reinhard et al. 2001]



Our method

Input



Our method



[Reinhard et al. 2001]



[Pitié et al. 2001]



Color Transform vs Color Distribution

- Our result is more golden

Input



Matched frame



Target frame at golden hour



Our result: use both frames



Photoshop color match: only use target frame



Application: continuous control



Containing videos

Application: translate the time of day of a painting



Input at day



Output at blue hour

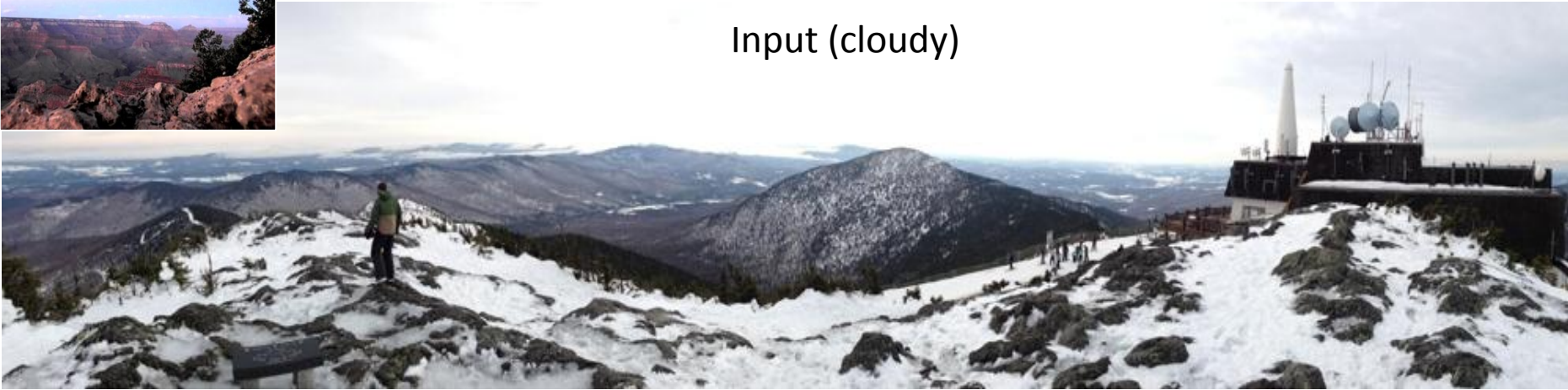
“In the Auvergne”, Jean-Francois Millet

Application: lighting transfer

Match frame



Input (cloudy)



Hand-picked target frame



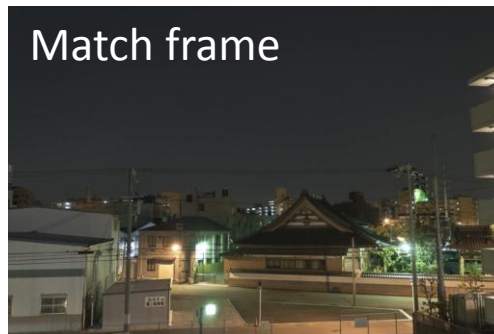
Light transfer (more sunshine)



Limitations

- Dynamic scenes are challenging
- We do not turn on lights
- Night-to-day case does not work well
- Plausible but not physically accurate

Night to Day



Output: color and shadow are wrong



Conclusion

- We introduce time hallucination: render an image at another time of day
- We use a time-lapse database, and propose a locally affine model to transfer the color change between two frames

Input



Output



Acknowledgments

- We thank Jianxiong Xiao for the help and advice in scene matching code, SIGGRAPH ASIA reviewers for their comments, and acknowledge the funding from NSF No.0964004 and NSF CGV-1111415.