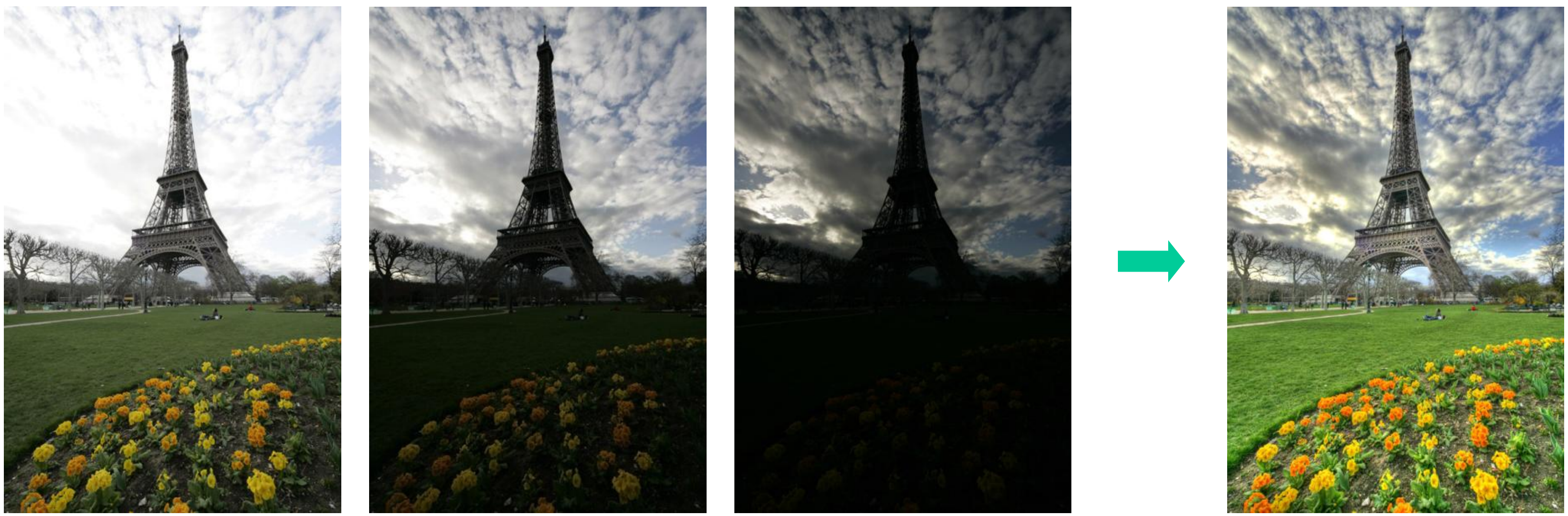
What have we leaned so far?

- Camera structure
- Eye structure



Project 1: High Dynamic Range Imaging

What have we learned so far?

- Image Filtering
- Image Warping
- Camera Projection Model

Project 2: Panoramic Image Stitching

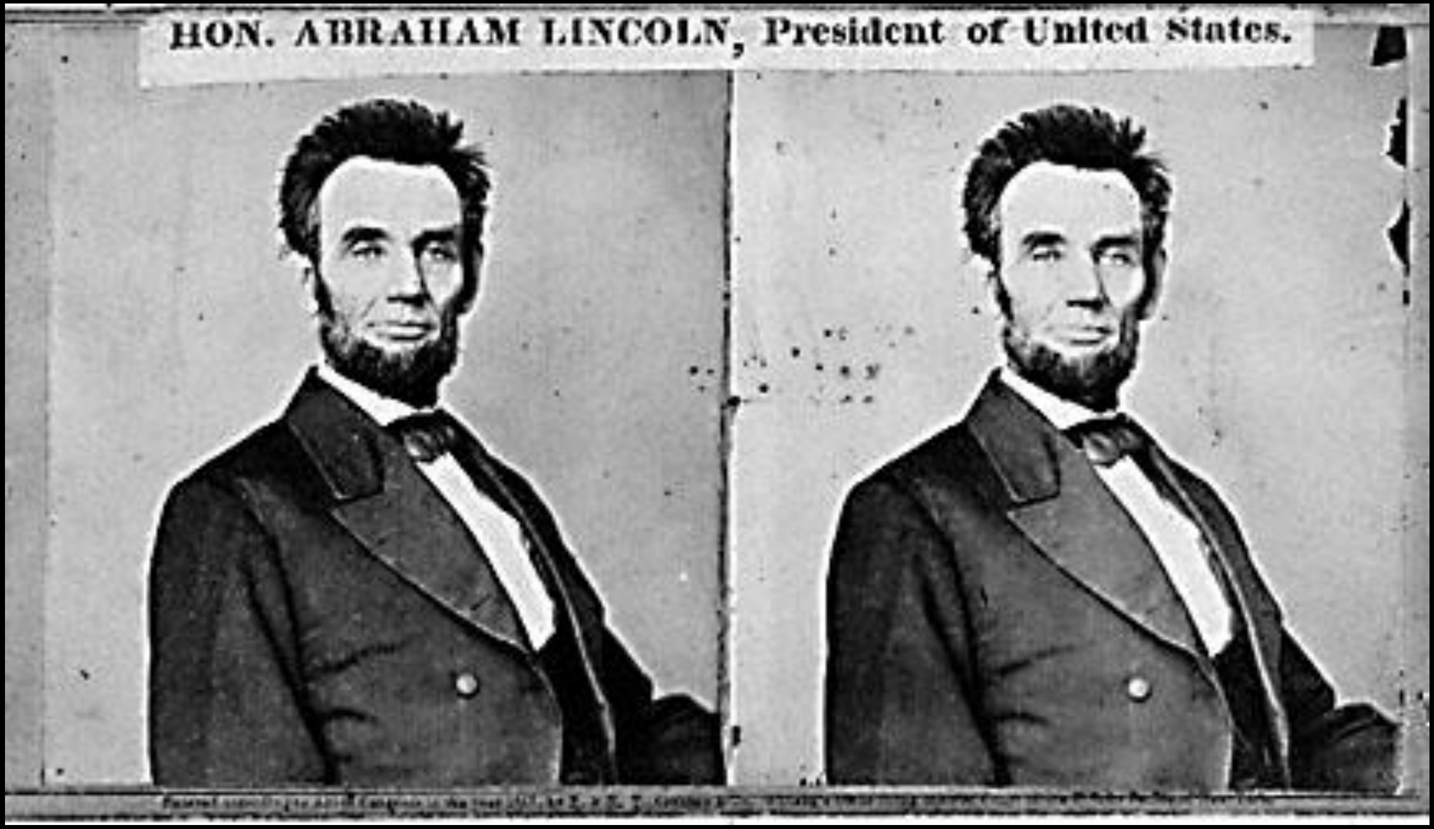
What have we learned so far?

- Projective Geometry
- Single View Modeling
- Shading Model

Project 3: Photometric Stereo

Today

- 3D modeling from two images – Stereo


HON. ABRAHAM LINCOLN, President of United States.

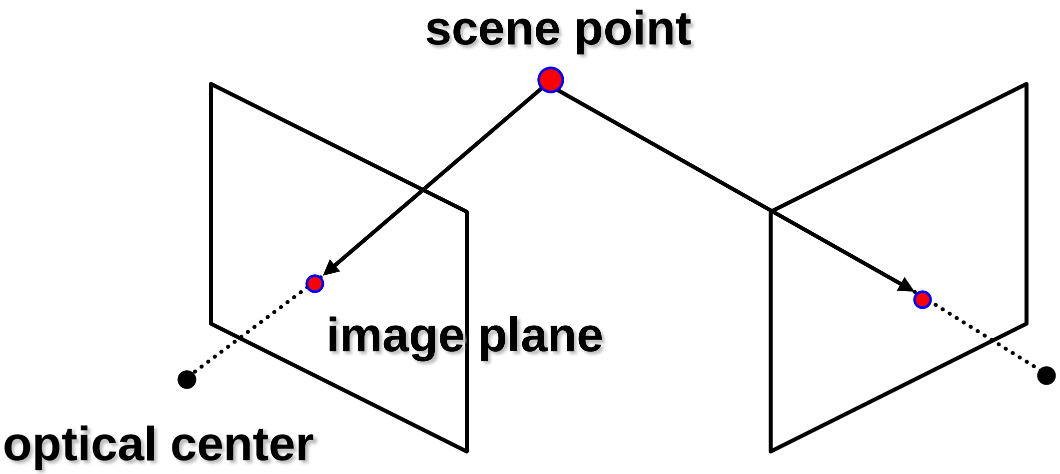
Public Library, Stereoscopic Looking Room, Chicago, by Phillips, 1923

Stereograms online

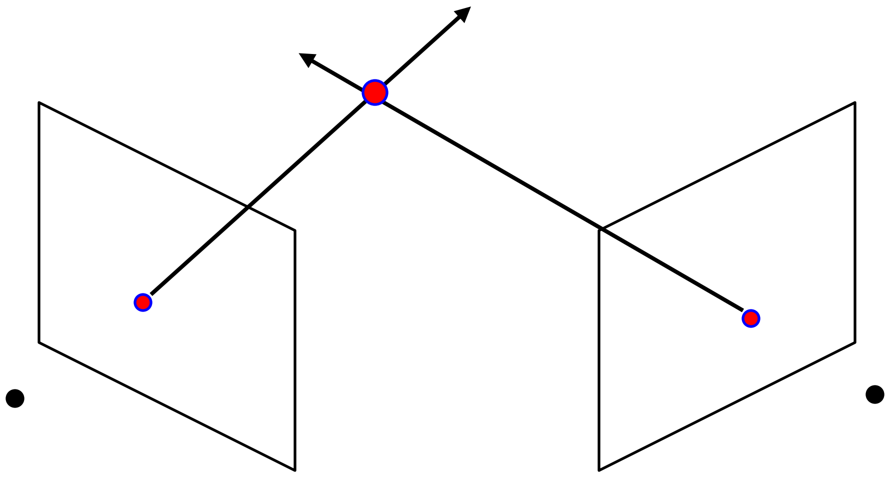
- UCR stereographs
  - http://www.cmp.ucr.edu/site/exhibitions/stereo/
- The Art of Stereo Photography
  - http://www.photostuff.co.uk/stereo.htm
- History of Stereo Photography
  - http://www.rpi.edu/~ruiz/stereo_history/text/historystereog.html
- Double Exposure
  - http://home.centurytel.net/s3dcor/index.html
- Stereo Photography
  - http://www.shortcourses.com/book01/chapter09.htm
- 3D Photography links
  - http://www.studyweb.com/links/5243.html
- National Stereoscopic Association
  - http://204.248.144.203/3dLibrary/welcome.html
- Books on Stereo Photography
  - http://userwww.sfsu.edu/~hl/3d.biblio.html

A free pair of red-blue stereo glasses can be ordered from Rainbow Symphony Inc
- http://www.rainbowsymphony.com/freestuff.html

Stereo



Stereo

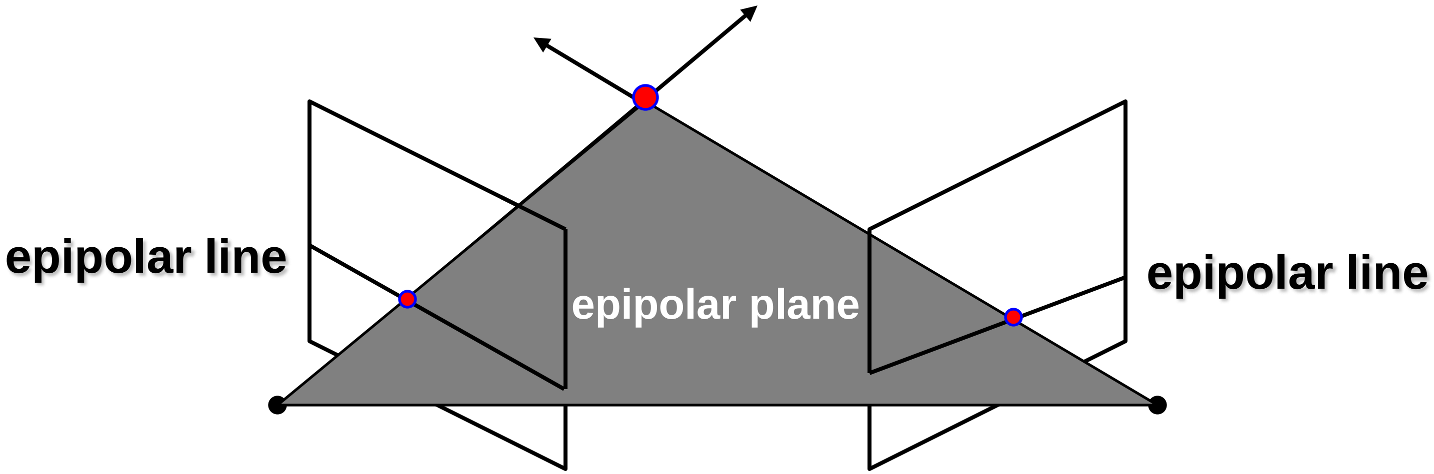


Basic Principle: Triangulation

- Gives reconstruction as intersection of two rays
- Requires
  - calibration
  - ***point correspondence***

Stereo correspondence

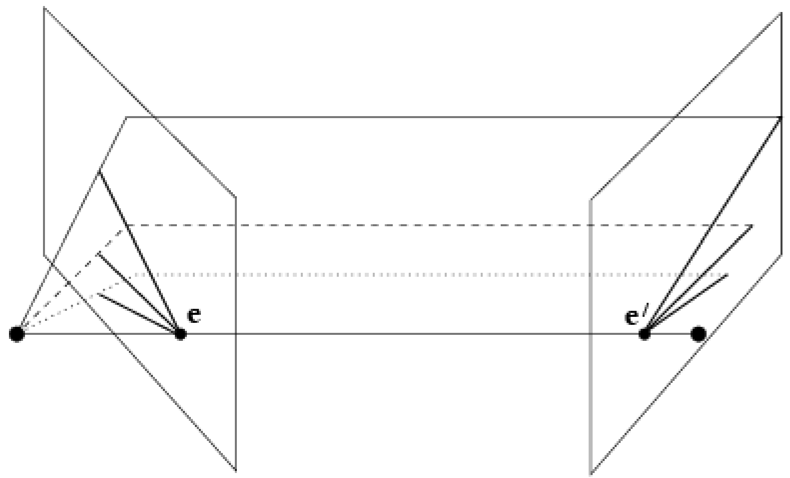
- Determine Pixel Correspondence
  - Pairs of points that correspond to same scene point

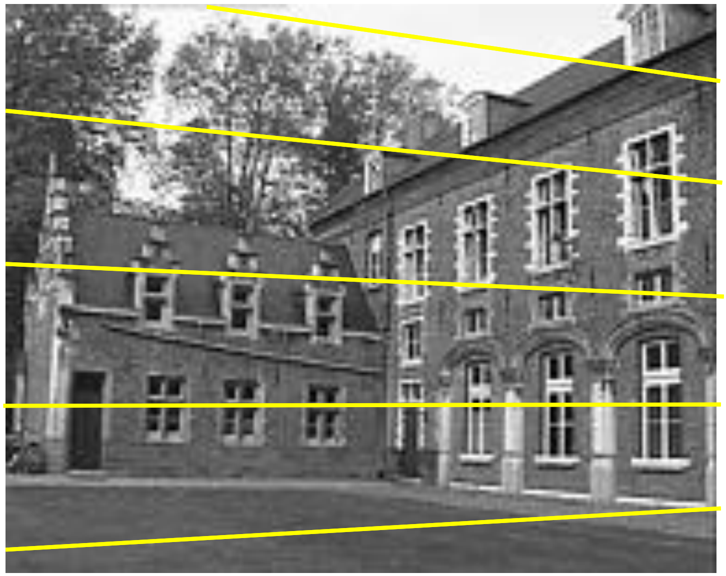


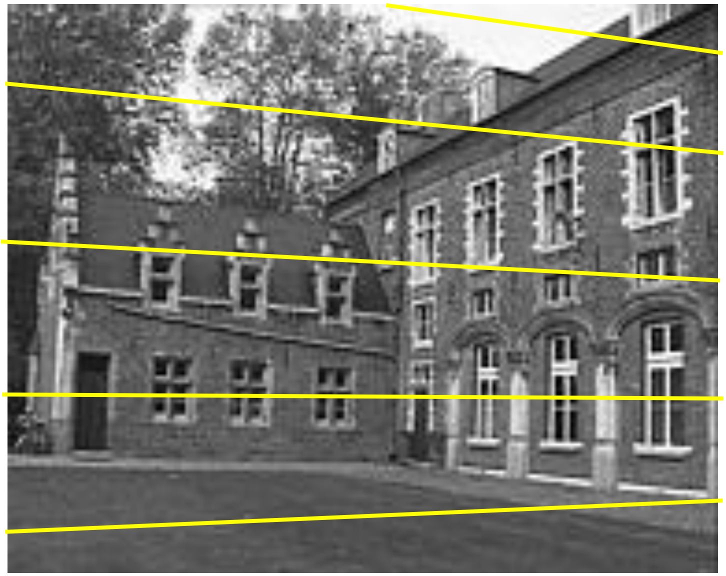
Epipolar Constraint

- Reduces correspondence problem to 1D search along *conjugate epipolar lines*
- Java demo: http://www.ai.sri.com/~luong/research/Meta3DViewer/EpipolarGeo.html

Epipolar Line Example

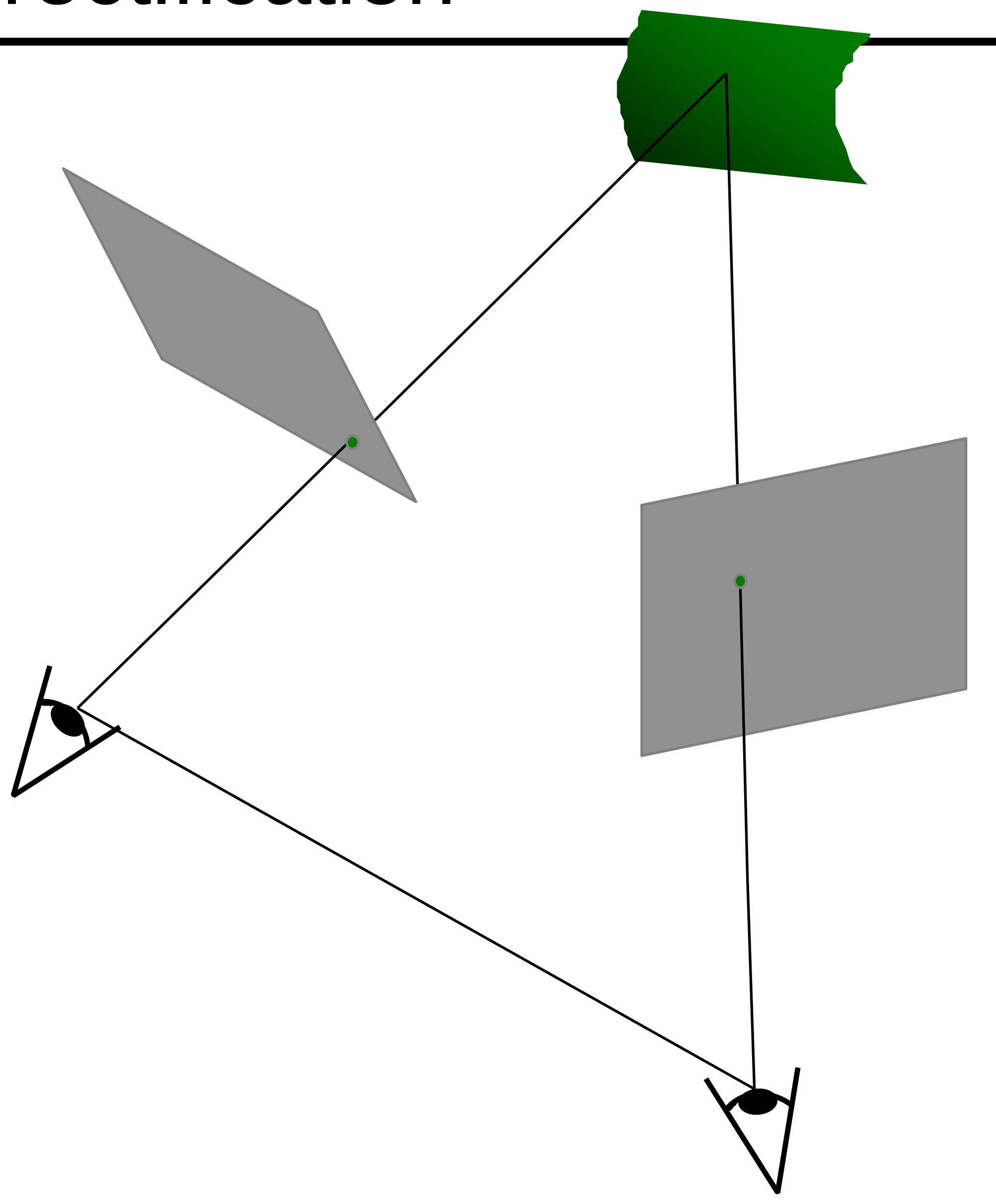




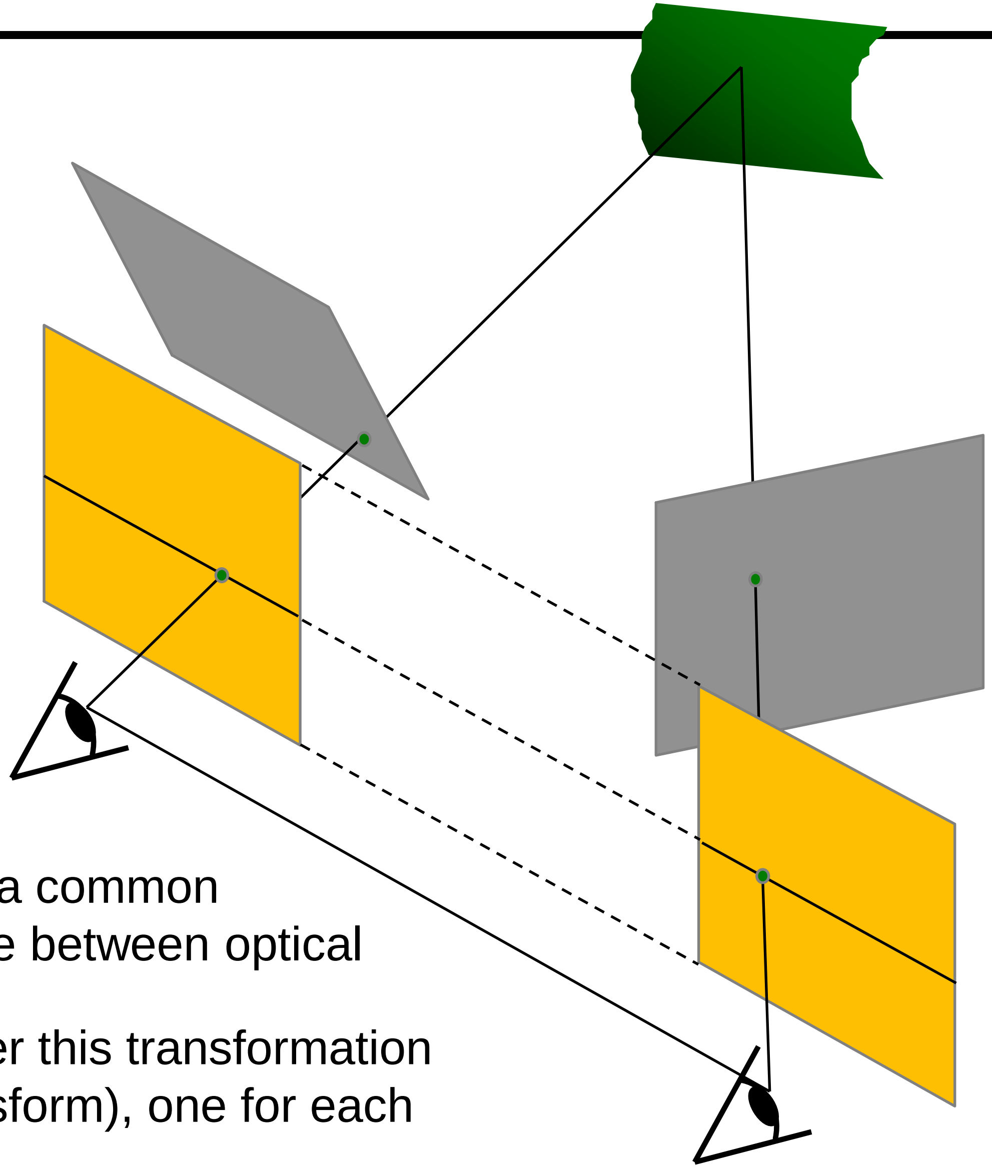


courtesy of Marc Pollefeys

Stereo image rectification



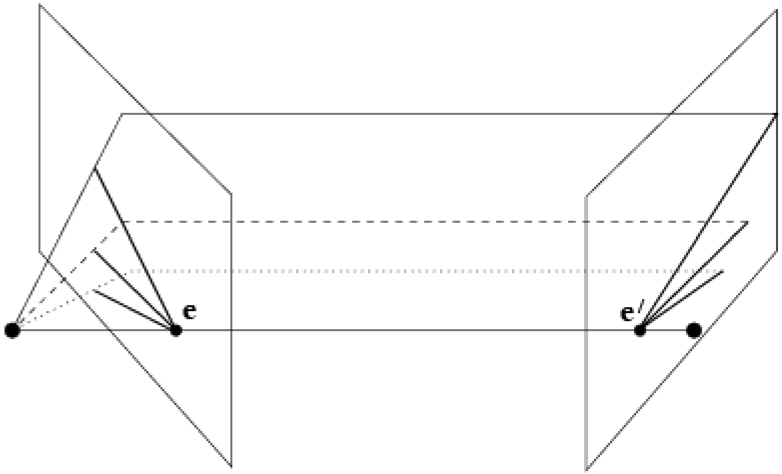
Stereo image rectification

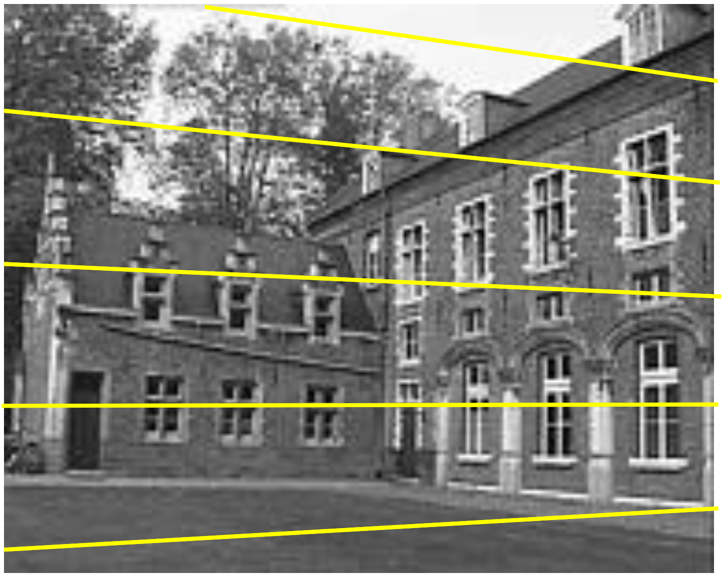


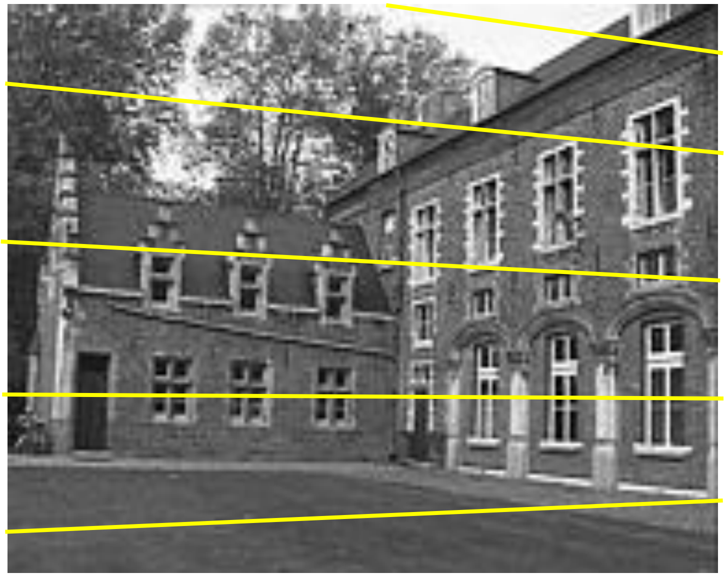
- reproject image planes onto a common
- plane parallel to the line between optical centers
- pixel motion is horizontal after this transformation
- two homographies (3x3 transform), one for each input image reprojection

➢ C. Loop and Z. Zhang. [Computing Rectifying Homographies for Stereo Vision](). IEEE Conf. Computer Vision and Pattern Recognition, 1999.

Epipolar Line Example

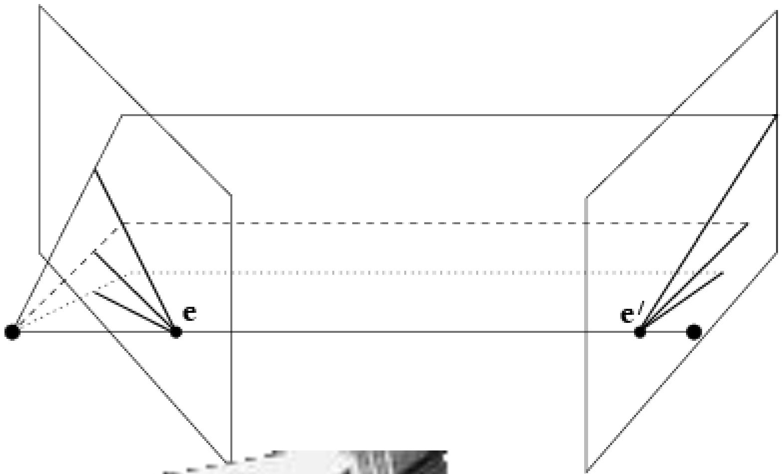


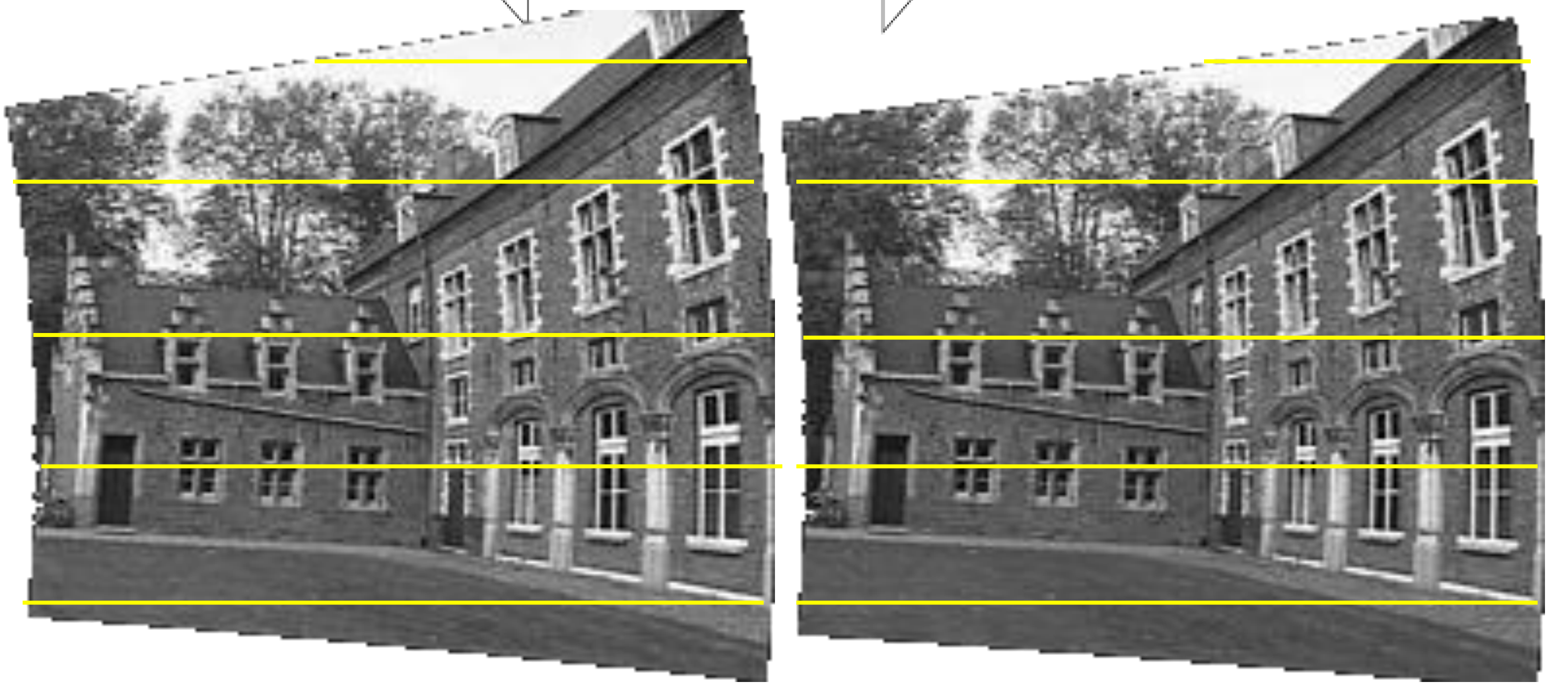




courtesy of Marc Pollefeys

Epipolar Line Example



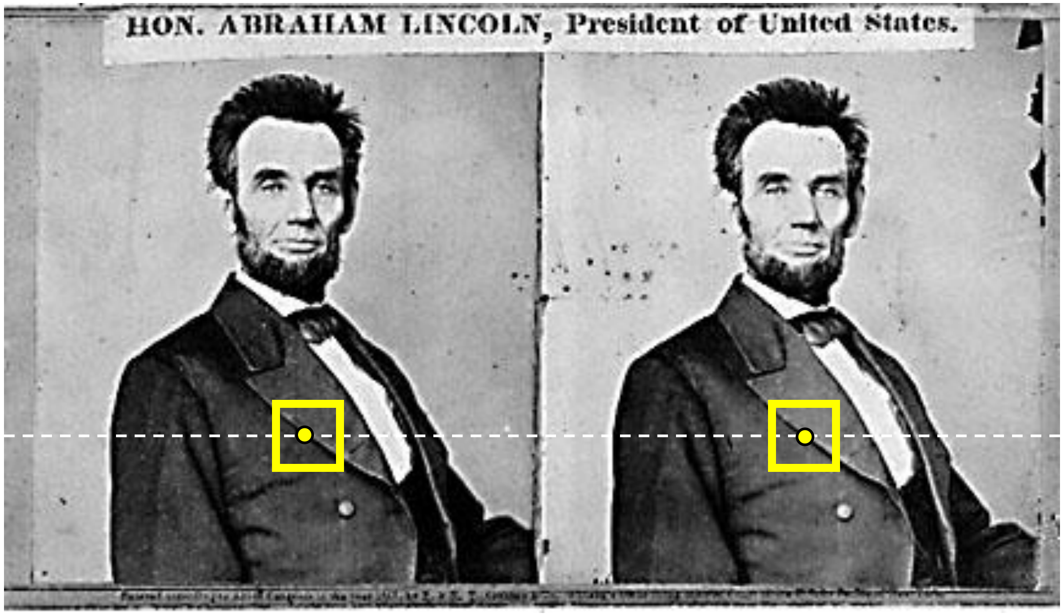


courtesy of Marc Pollefeys

Stereo matching algorithms

- Match Pixels in Conjugate Epipolar Lines
  - Assume brightness constancy
  - This is a tough problem
  - Numerous approaches
    - A good survey and evaluation: http://www.middlebury.edu/stereo/

Basic stereo algorithm



For each epipolar line

For each pixel in the left image

- compare with every pixel on same epipolar line in right image
- pick pixel with minimum match cost

Improvement: match *windows*

Basic stereo algorithm

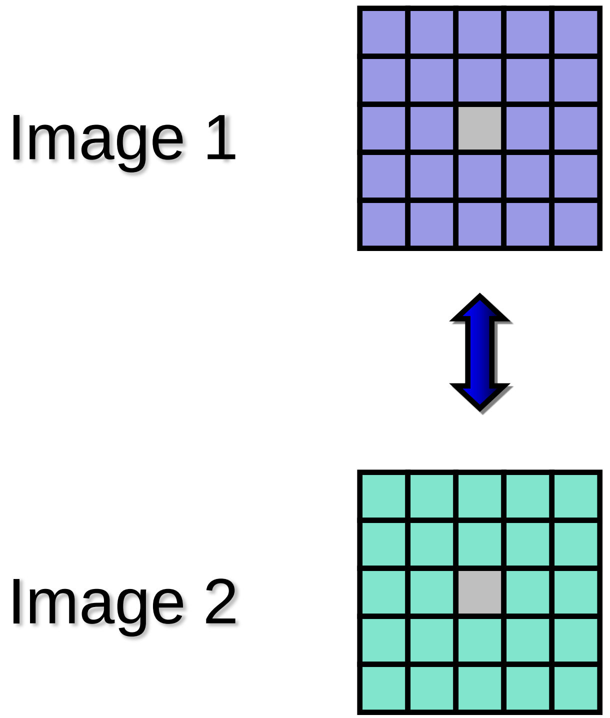
- For each pixel
  - For each disparity
    - For each pixel in window
      - » Compute difference
  - Find disparity with minimum SSD

Reverse order of loops

- For each disparity
  - For each pixel
    - For each pixel in window
      - Compute difference
- Find disparity with minimum SSD at each pixel

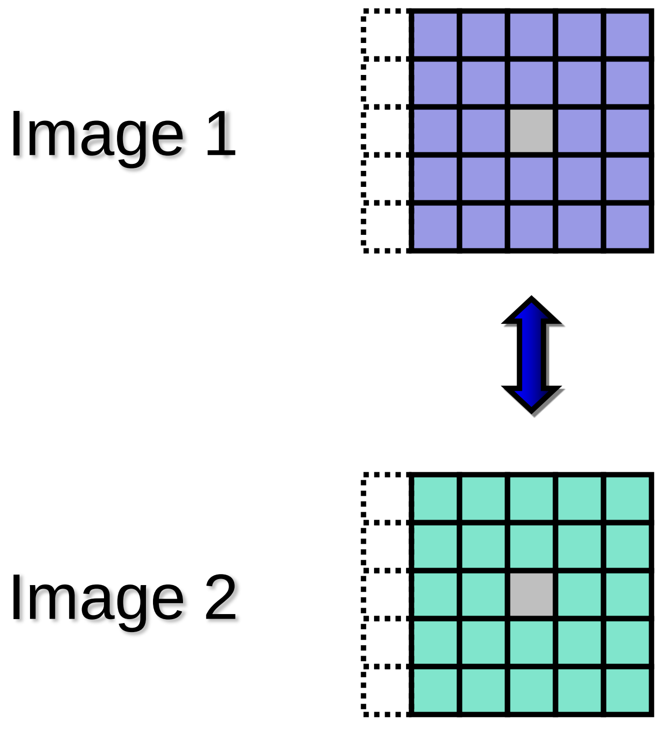
Incremental computation

- Given SSD of a window, at some disparity



Incremental computation

- Want: SSD at next location



Incremental computation

- Subtract contributions from leftmost column, add contributions from rightmost column

Image 1

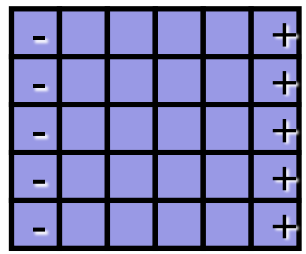
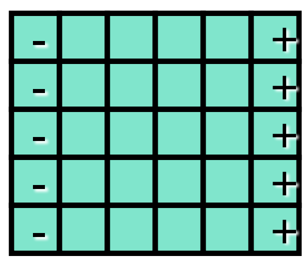


Image 2

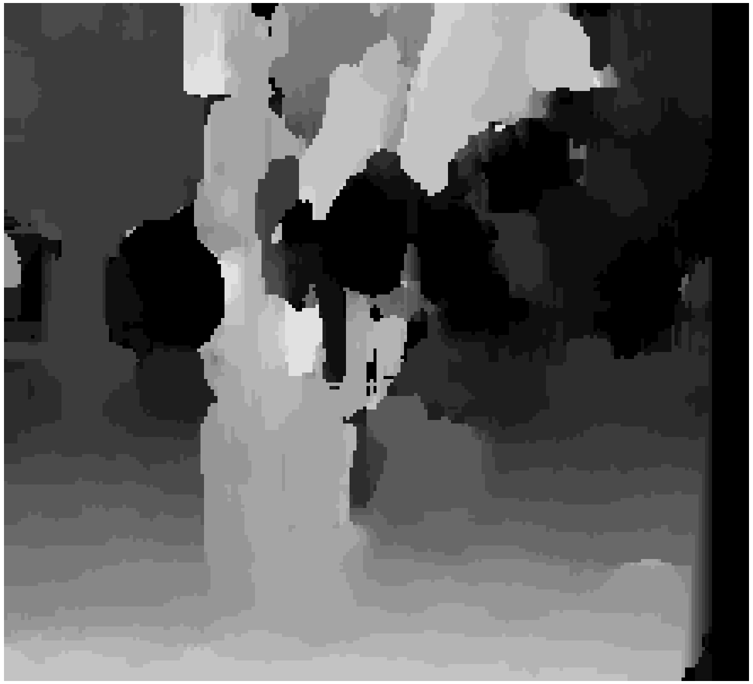


Selecting window size

- Small window: more detail, but more noise
- Large window: more robustness, less detail
- Example:

Selecting window size

3 pixel window



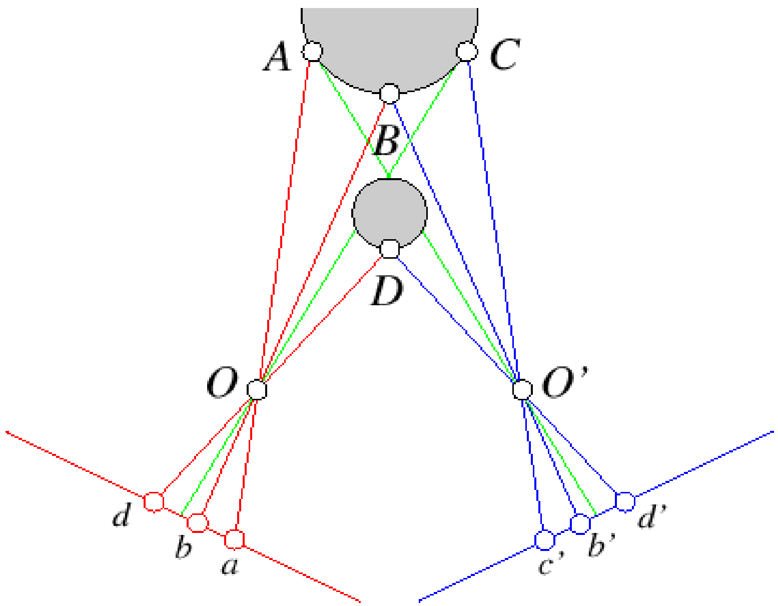
20 pixel window

Non-square windows

- Compromise: have a large window, but higher weight near the center
- Example: Gaussian
- Example: Shifted windows

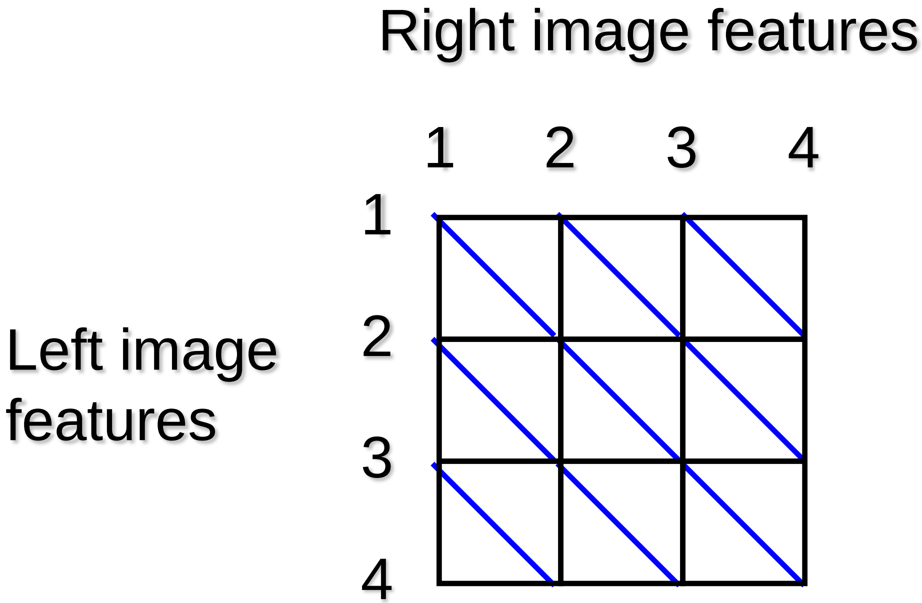

Ordering constraint

- Order of matching features usually the same in both images
- But not always: occlusion



Dynamic programming

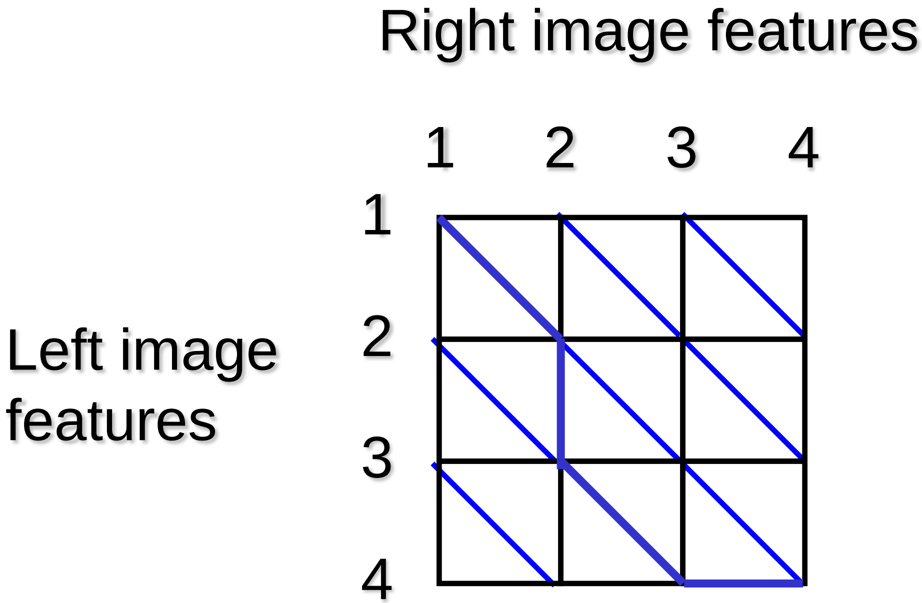
- Treat feature correspondence as graph problem

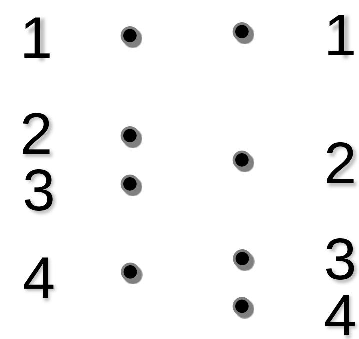


Cost of edges = similarity of regions between image features

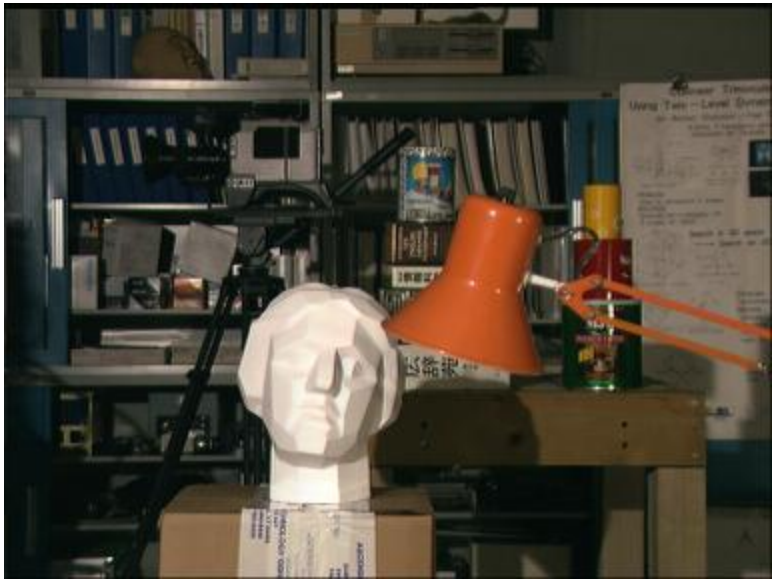
Dynamic programming

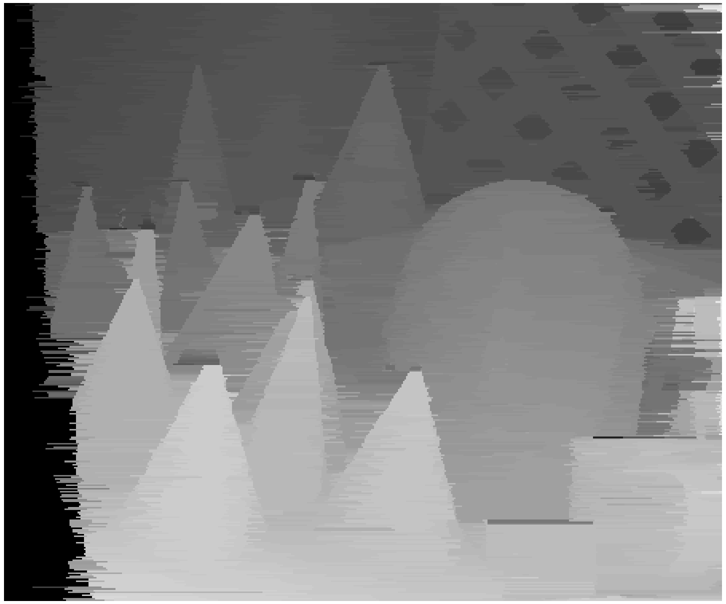
- Find min-cost path through graph





Dynamic Programming Results



Energy minimization

- Another approach to improve quality of correspondences
- Assumption: disparities vary (mostly) smoothly
- Minimize energy function:

$$E_{data} + \lambda E_{smoothness}$$

- E_{data}: how well does disparity match data
- $E_{smoothness}$: how well does disparity match that of neighbors – regularization

Stereo as energy minimization

- Matching Cost Formulated as Energy
  - "data" term penalizing bad matches

$$D(x, y, d) = \left|\mathbf{I}(x, y) - \mathbf{J}(x+d, y)\right|$$

  - "neighborhood term" encouraging spatial smoothness

$$V(d_1, d_2) = \text{cost of adjacent pixels with labels d1 and d2}$$

$$= \left|d_1 - d_2\right| \quad \text{(or something similar)}$$

$$E = \sum_{(x,y)} D(x, y, d_{x,y}) + \sum_{neighbors\ (x1,y1),(x2,y2)} V(d_{x1,y1}, d_{x2,y2})$$

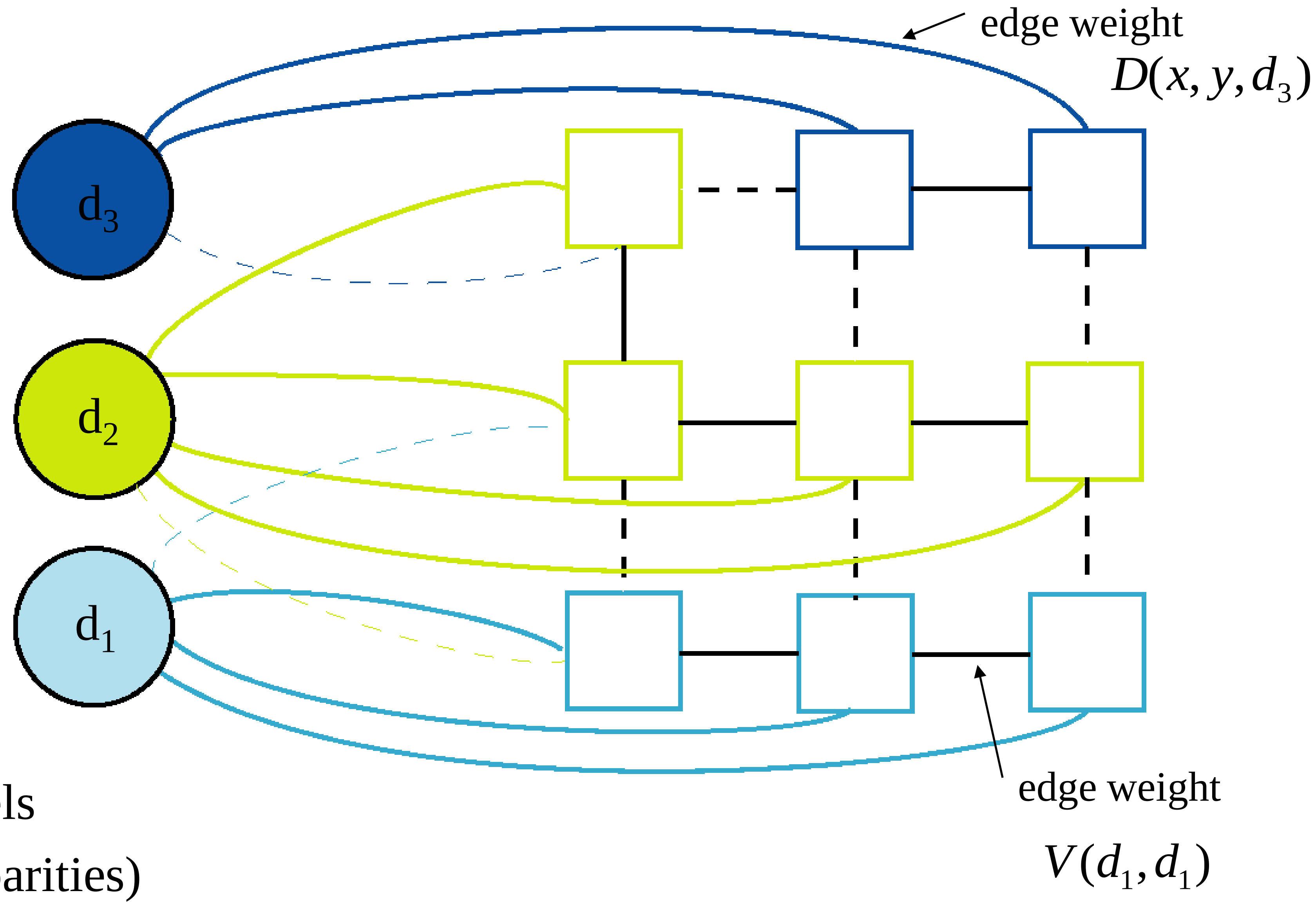
Energy minimization

- If data and energy terms are nice (continuous, smooth, etc.) can try to minimize via gradient descent, etc.
- In practice, disparities only piecewise smooth
- Design smoothness function that doesn't penalize large jumps too much
  - Example: $V(\alpha,\beta)=\min(|\alpha-\beta|, K)$

Energy minimization

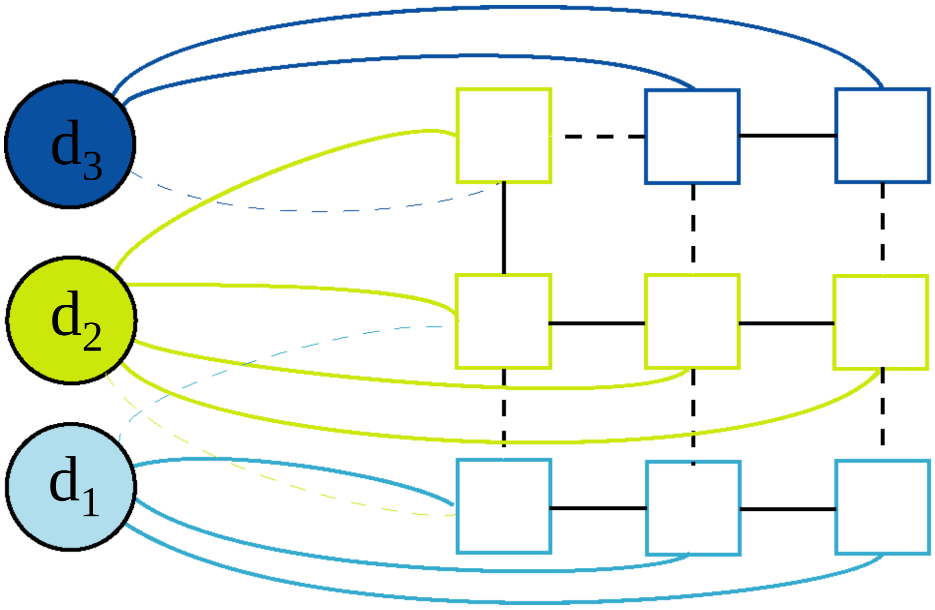
- Hard to find global minima of non-smooth functions
  - Many local minima
  - Provably NP-hard
- Practical algorithms look for approximate minima (e.g., simulated annealing)

Energy minimization via graph cuts



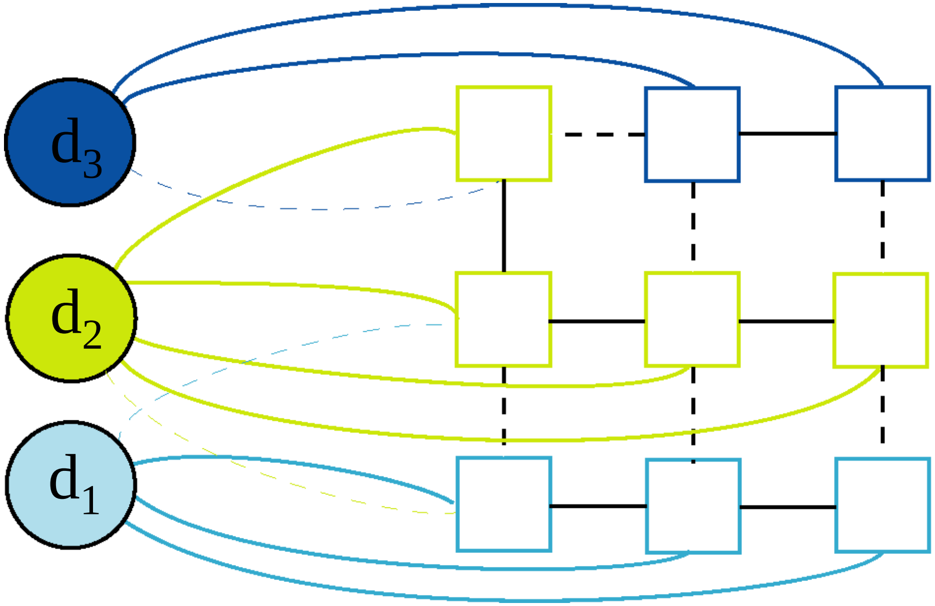
Labels
(disparities)

Energy minimization via graph cuts



- Graph Cost
  - Matching cost between images
  - Neighborhood matching term
  - Goal: figure out which labels are connected to which pixels

Energy minimization via graph cuts



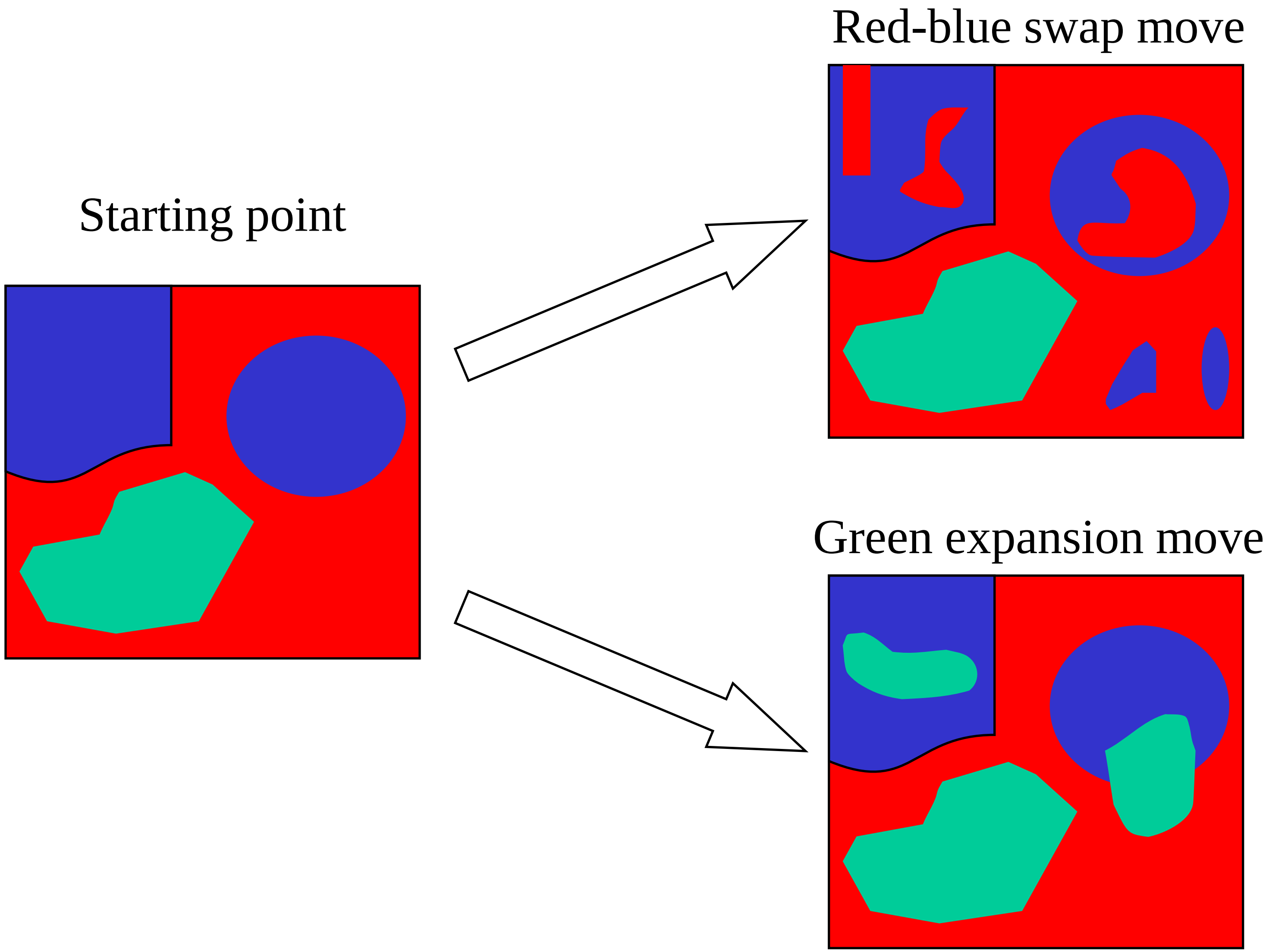
- Graph Cut
  - Delete enough edges so that
    - each pixel is (transitively) connected to exactly one label node
  - Cost of a cut: sum of deleted edge weights
  - Finding min cost cut equivalent to finding global minimum of energy function

Computing a multiway cut

- With 2 labels: classical min-cut problem
  - Solvable by standard flow algorithms
    - polynomial time in theory, nearly linear in practice
  - More than 2 terminals: NP-hard

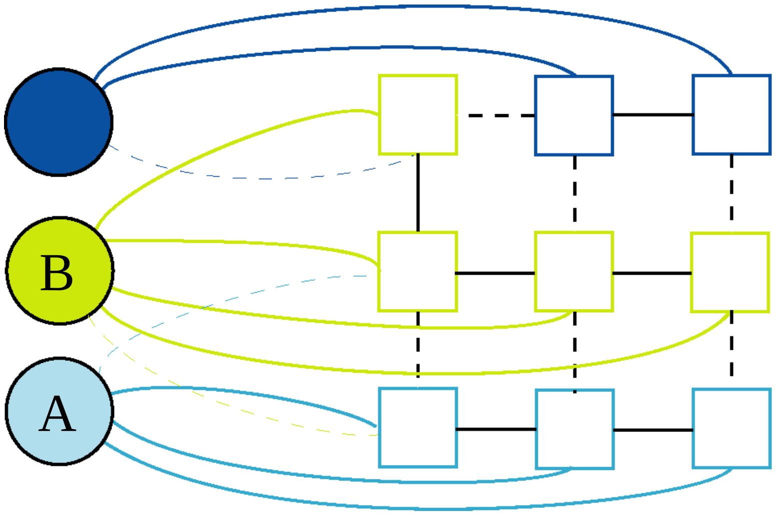
    [Dahlhaus *et al.*, STOC '92]
- Efficient approximation algorithms exist
  - Within a factor of 2 of optimal
  - Computes local minimum in a strong sense
    - even very large moves will not improve the energy
  - Yuri Boykov, Olga Veksler and Ramin Zabih, Fast Approximate Energy Minimization via Graph Cuts, International Conference on Computer Vision, September 1999.

Move examples

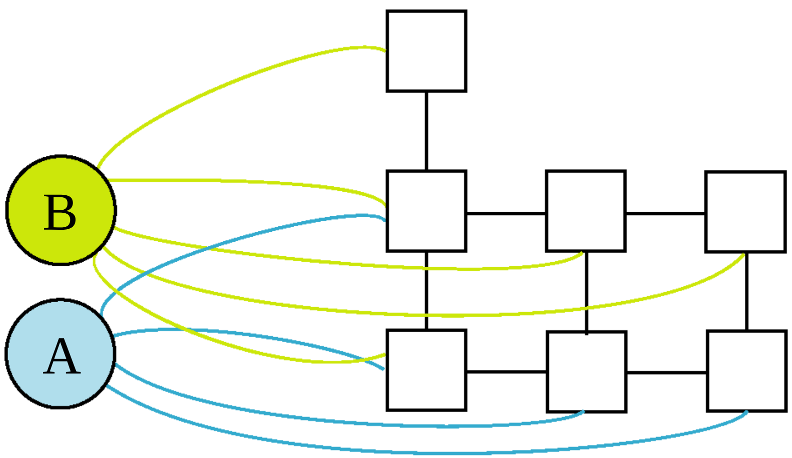


The swap move algorithm

1. Start with an arbitrary labeling
2. Cycle through every label pair *(A,B)* in some order
   - 2.1 Find the lowest *E* labeling within a single *AB*-swap
   - 2.2 Go there if it's lower *E* than the current labeling
3. If *E* did not decrease in the cycle, we're done
   Otherwise, go to step 2



Original graph



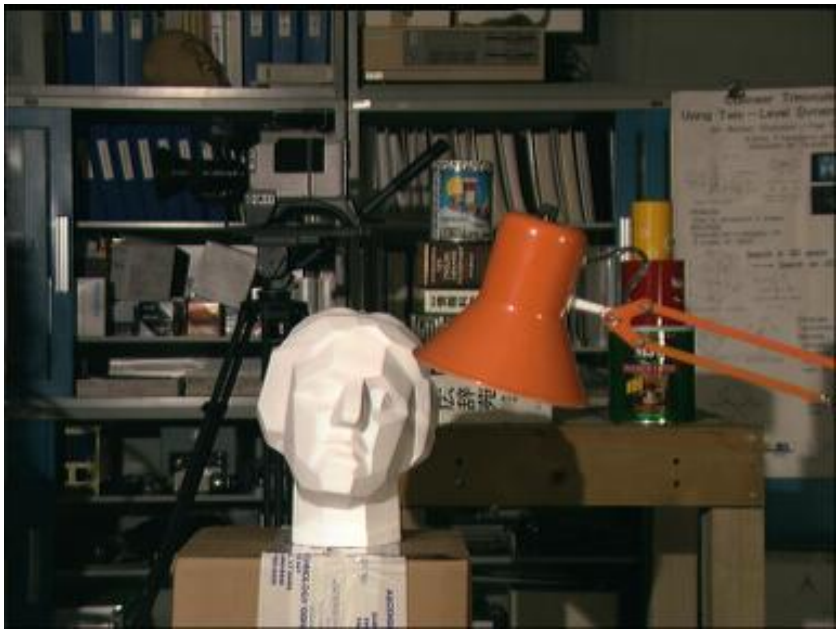
AB subgraph
(run min-cut on this graph)

The expansion move algorithm

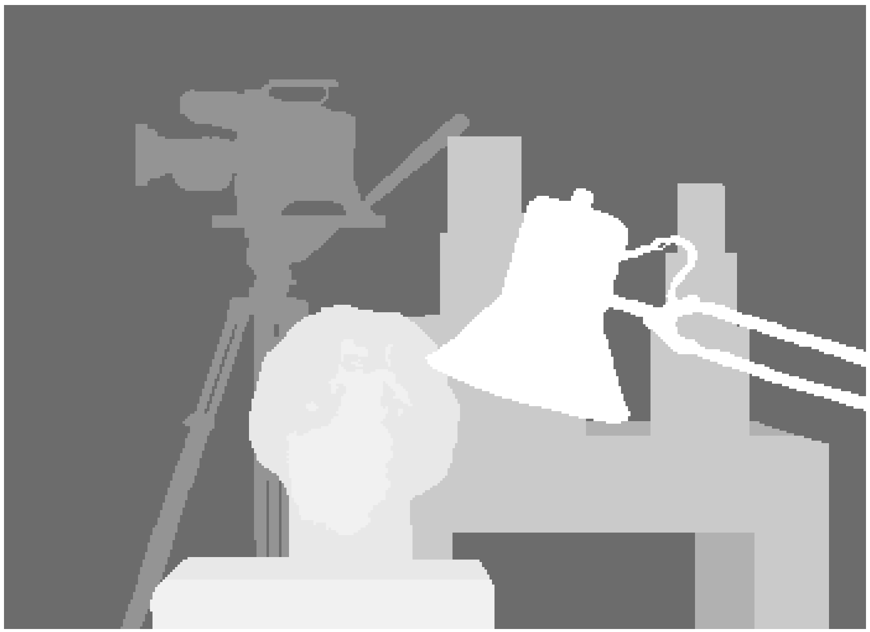
1. Start with an arbitrary labeling
2. Cycle through every label *A* in some order
   2.1 Find the lowest *E* labeling within a single *A*-expansion
   2.2 Go there if it's lower *E* than the current labeling
3. If *E* did not decrease in the cycle, we're done Otherwise, go to step 2

Stereo results

- Data from University of Tsukuba



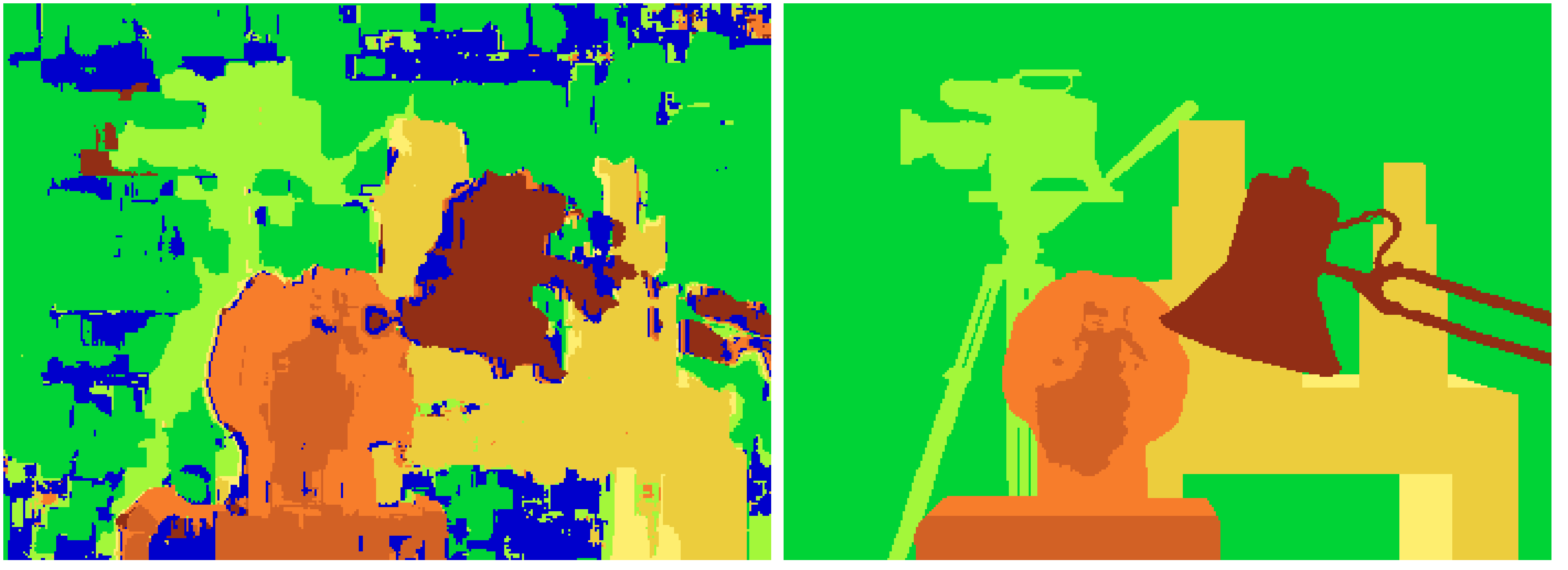
scene



ground truth

http://cat.middlebury.edu/stereo/

Results with window correlation



normalized correlation
(best window size)

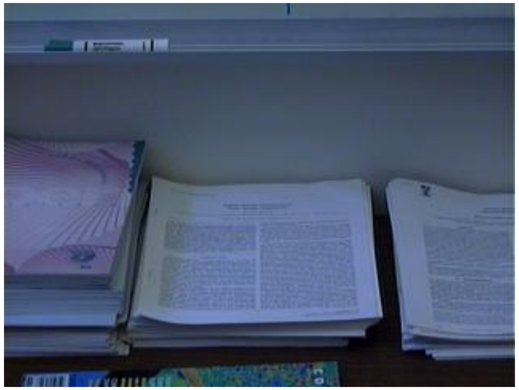
ground truth

Results with graph cuts

graph cuts
(Potts model *E*,
expansion move algorithm)

ground truth

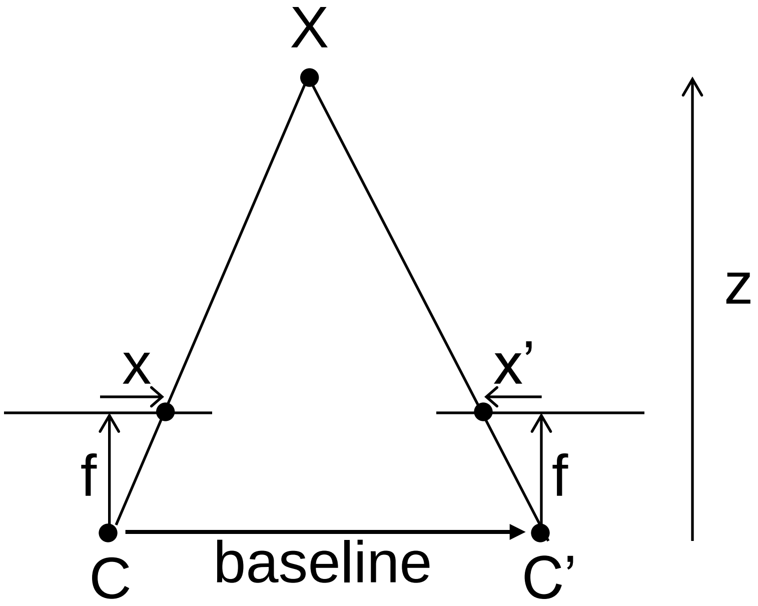
Depth from disparity



input image (1 of 2)

depth map
[Szeliski & Kang '95]

3D rendering



$$disparity = x - x' = \frac{baseline * f}{z}$$

Real-time stereo

Nomad robot searches for meteorites in Antartica
http://www.frc.ri.cmu.edu/projects/meteorobot/index.html

- Used for robot navigation (and other tasks)
  - Several software-based real-time stereo techniques have been developed (most based on simple discrete search)

Stereo reconstruction pipeline

- Steps
  - Calibrate cameras
  - Rectify images
  - Compute disparity
  - Estimate depth

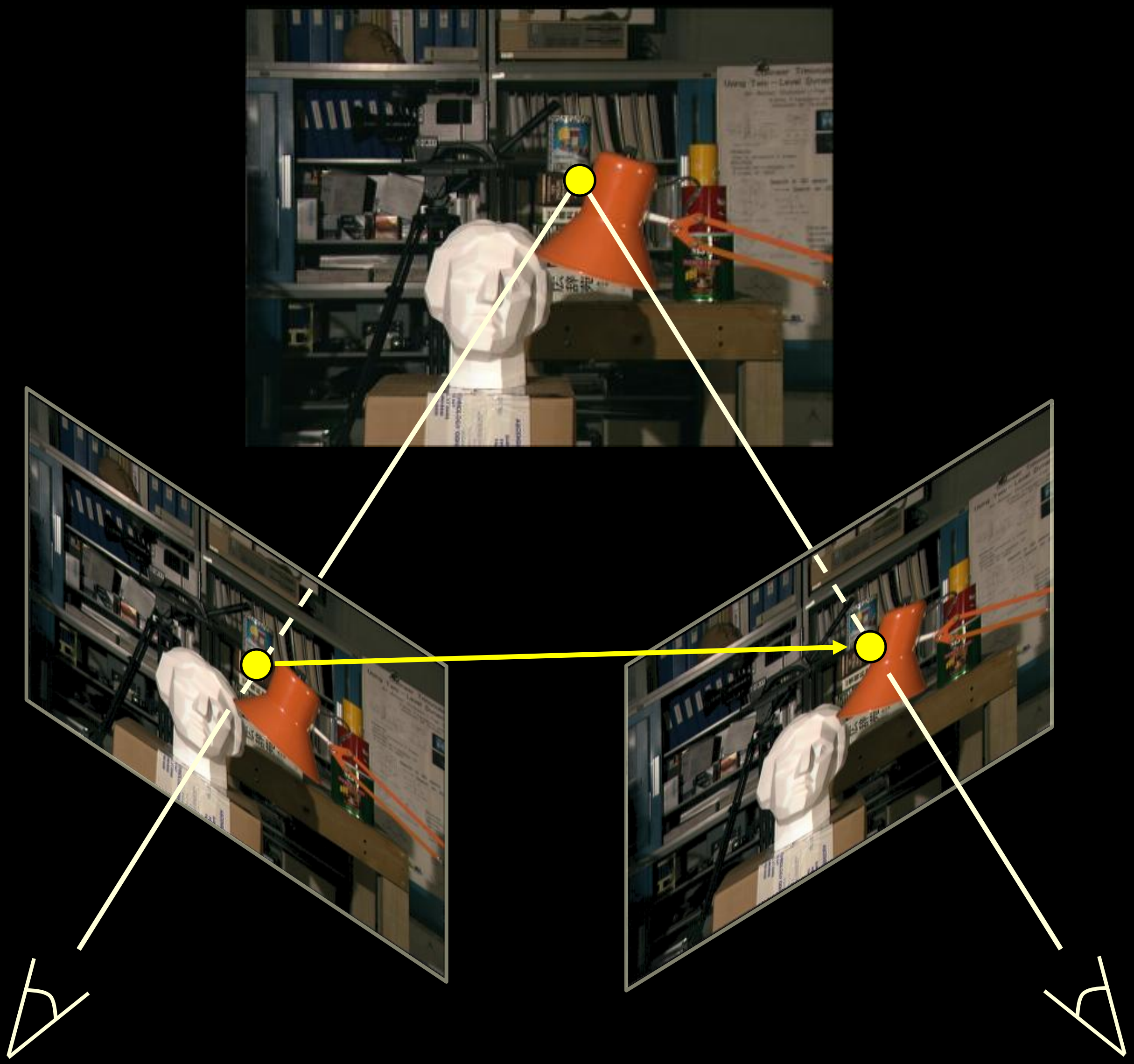
What will cause errors?

- Camera calibration errors
- Poor image resolution
- Occlusions
- Violations of brightness constancy (specular reflections)
- Large motions
- Low-contrast image regions

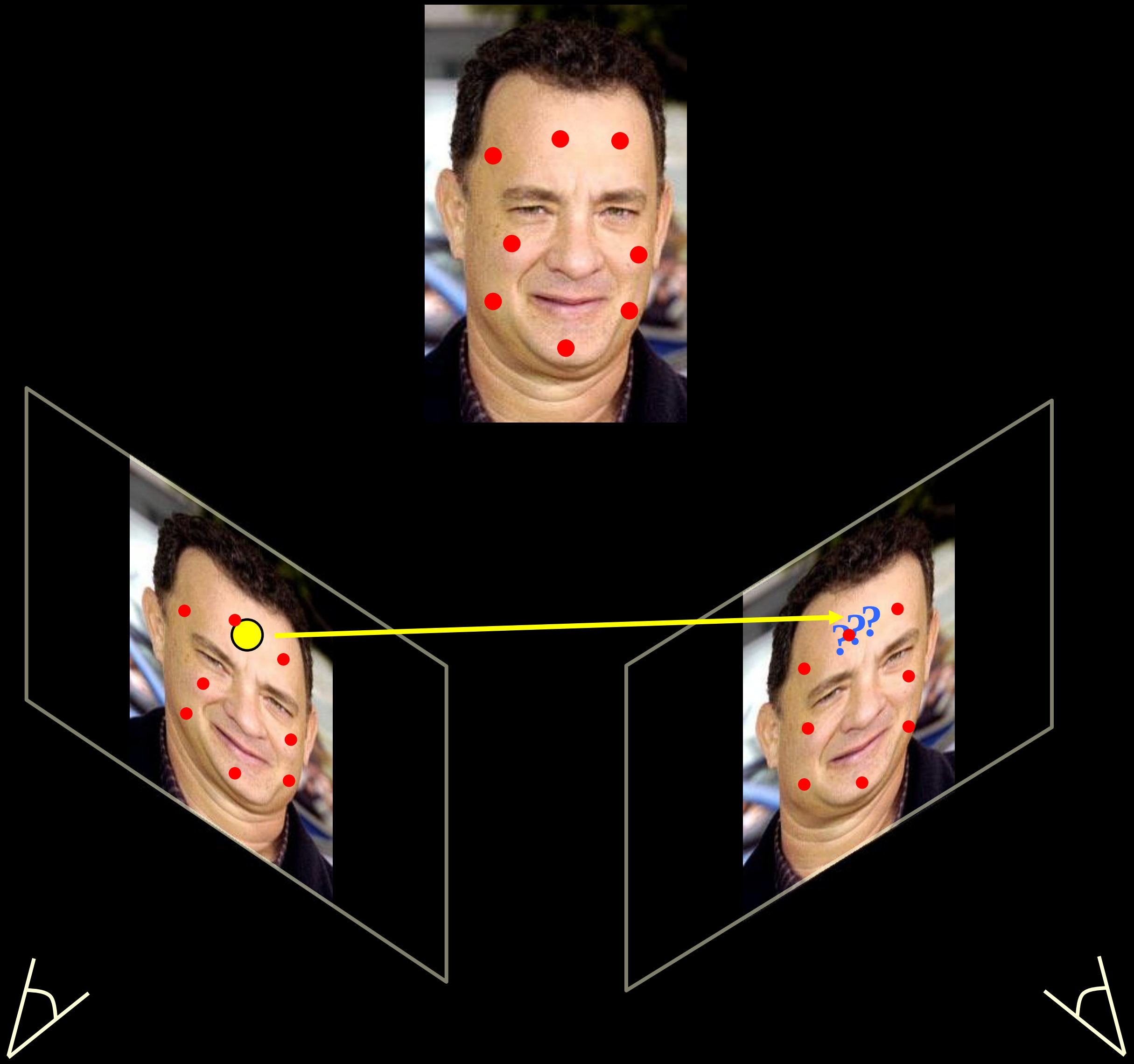
Spacetime Stereo

Li Zhang, Noah Snavely, Brian Curless, Steven Seitz
CVPR 2003, SIGGRAPH 2004

Stereo



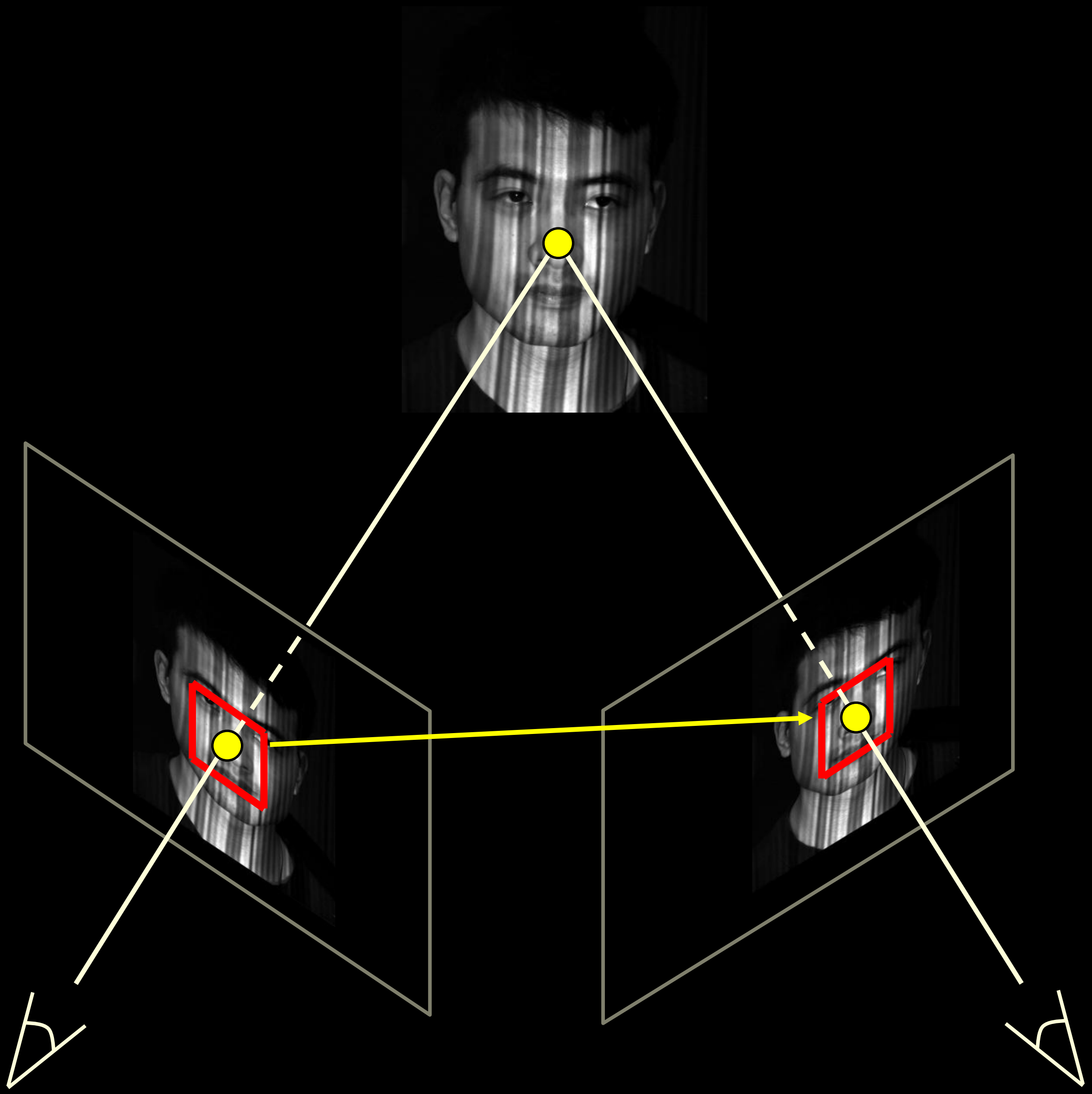
Stereo



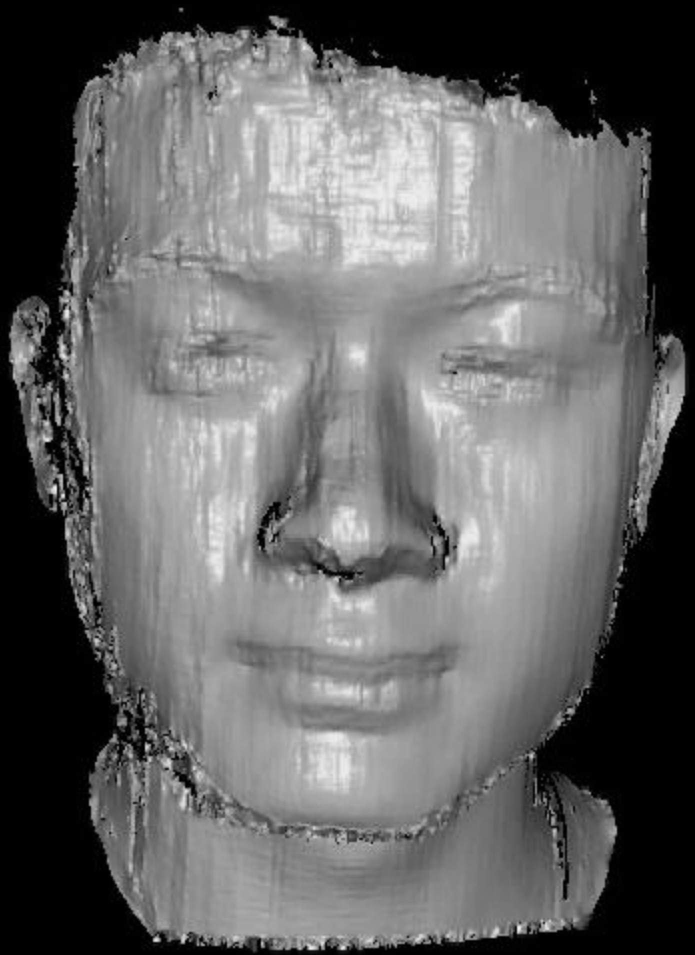
Marker-based Face Capture

"The largest intractable problem with 'The Polar Express' is that the motion-capture technology used to create the human figures has resulted in a film filled with creepily unlifelike beings."

Stereo

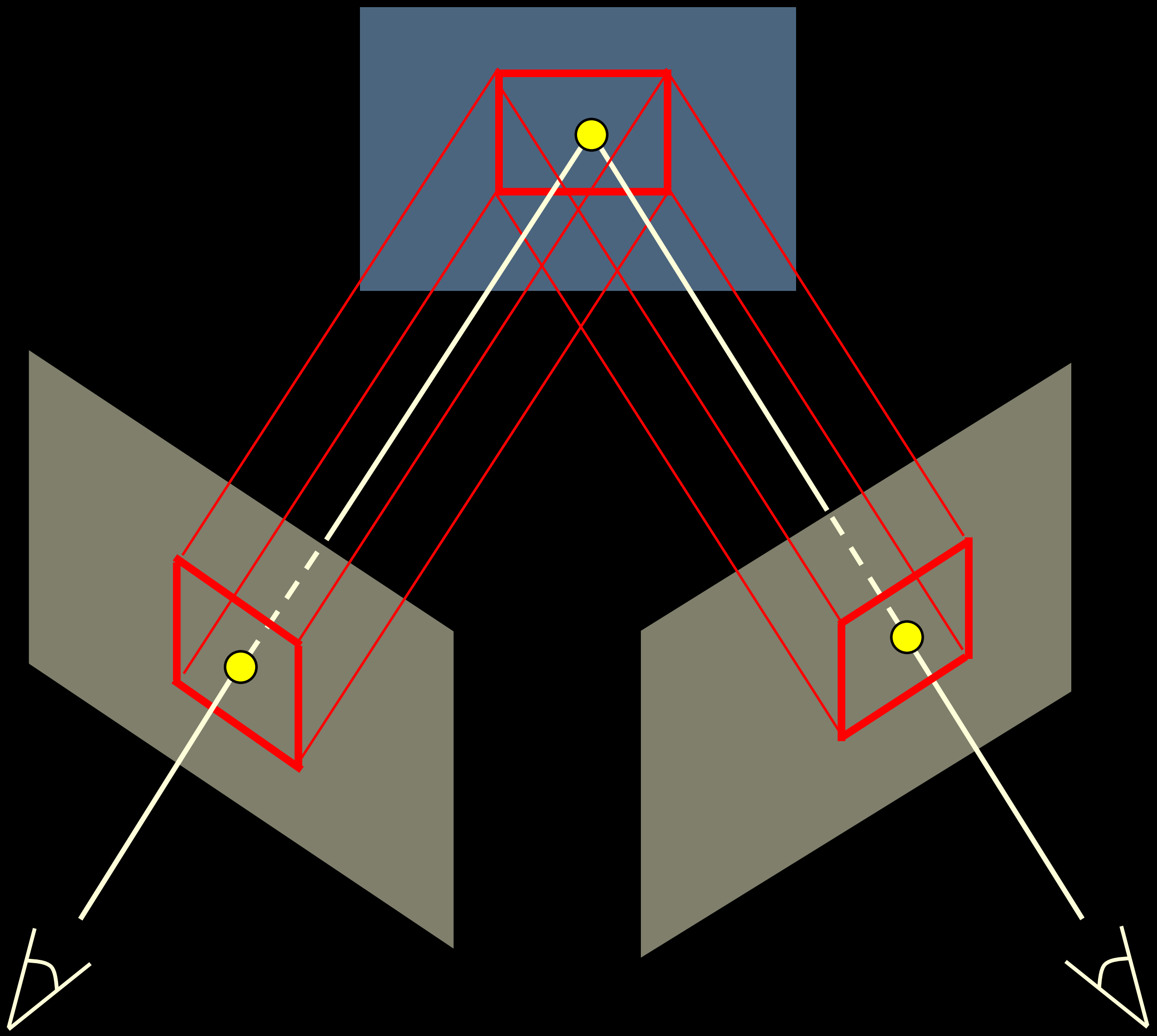


Stereo

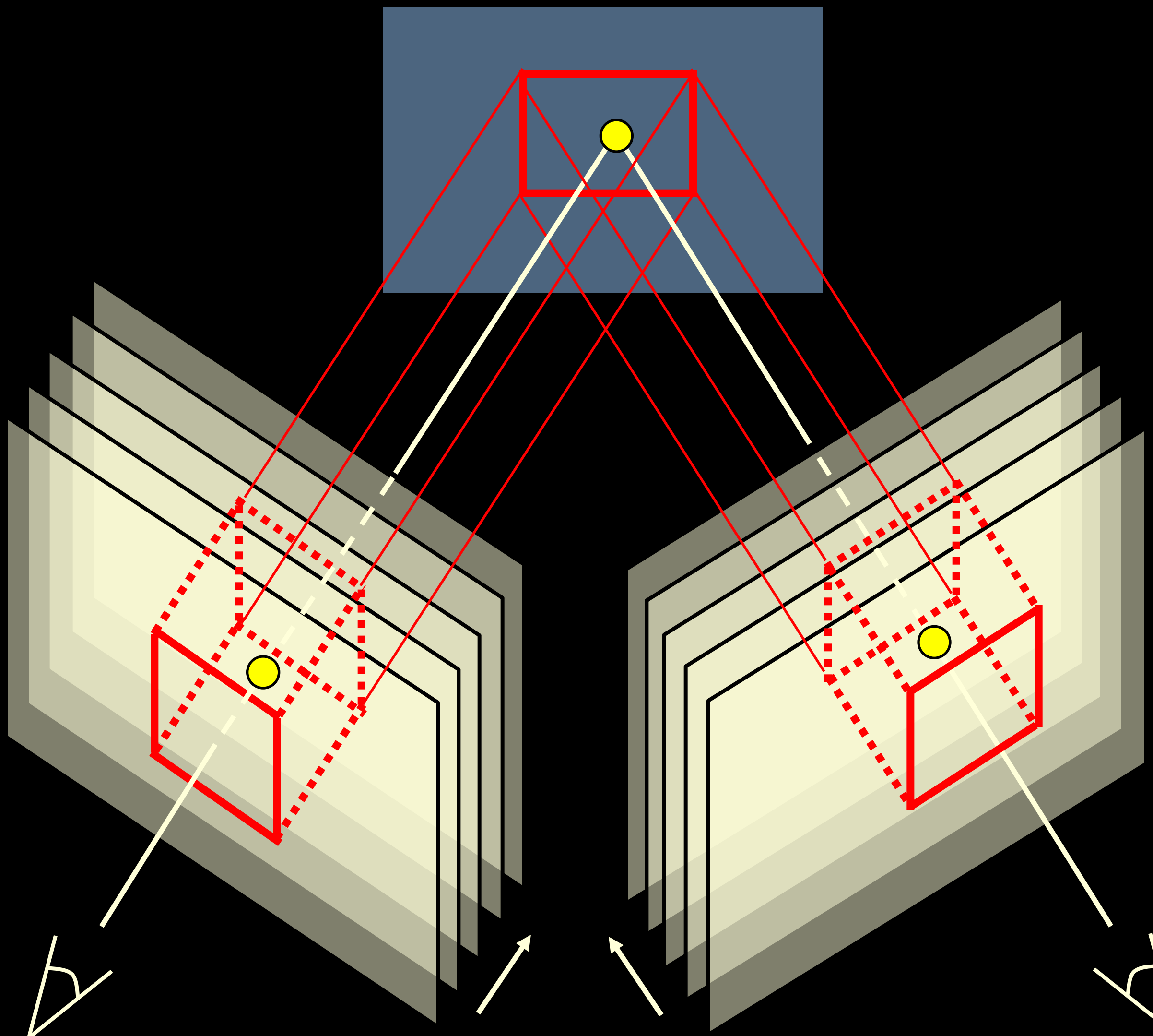


Inaccurate & Jittering

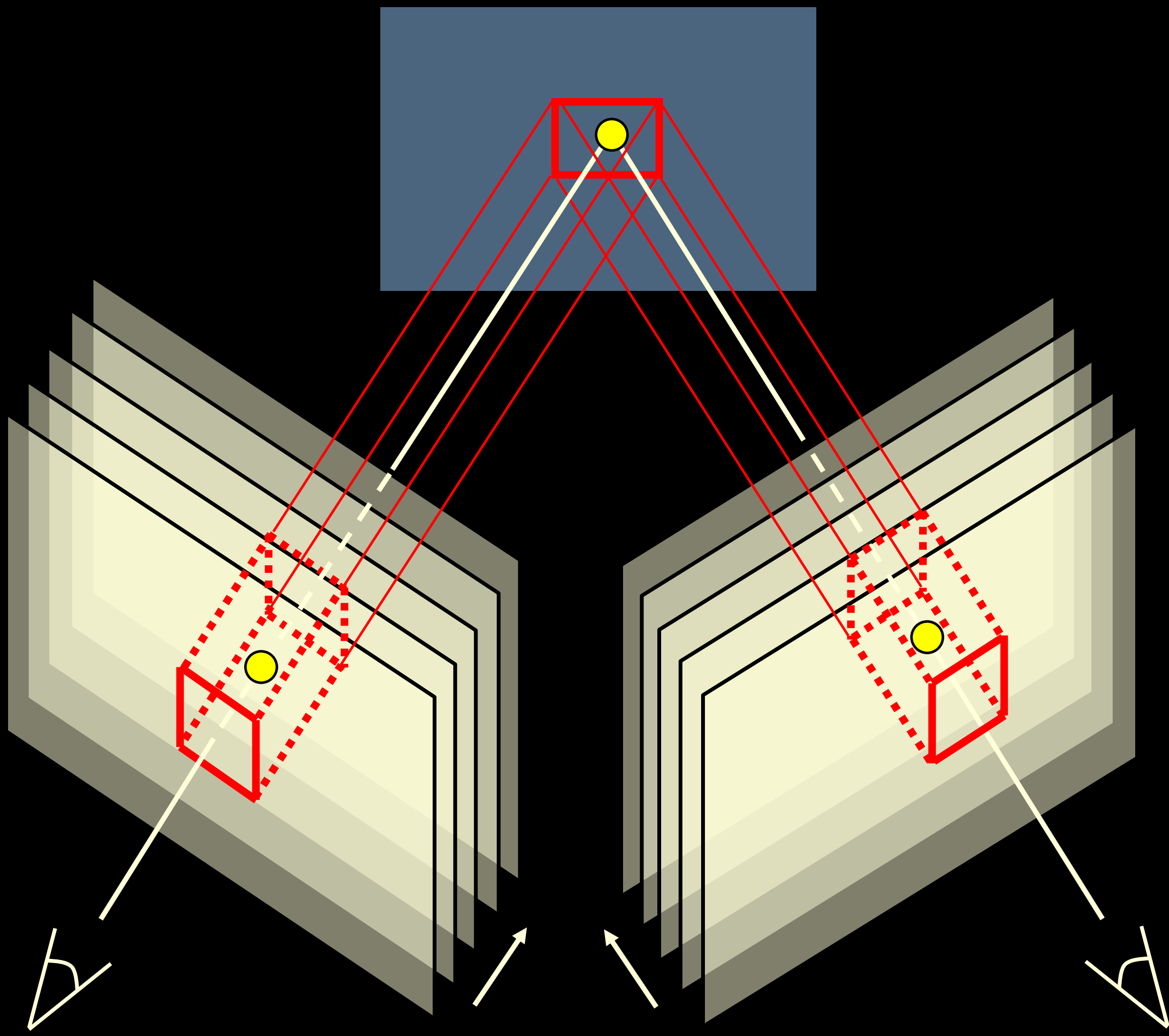
Spacetime Stereo



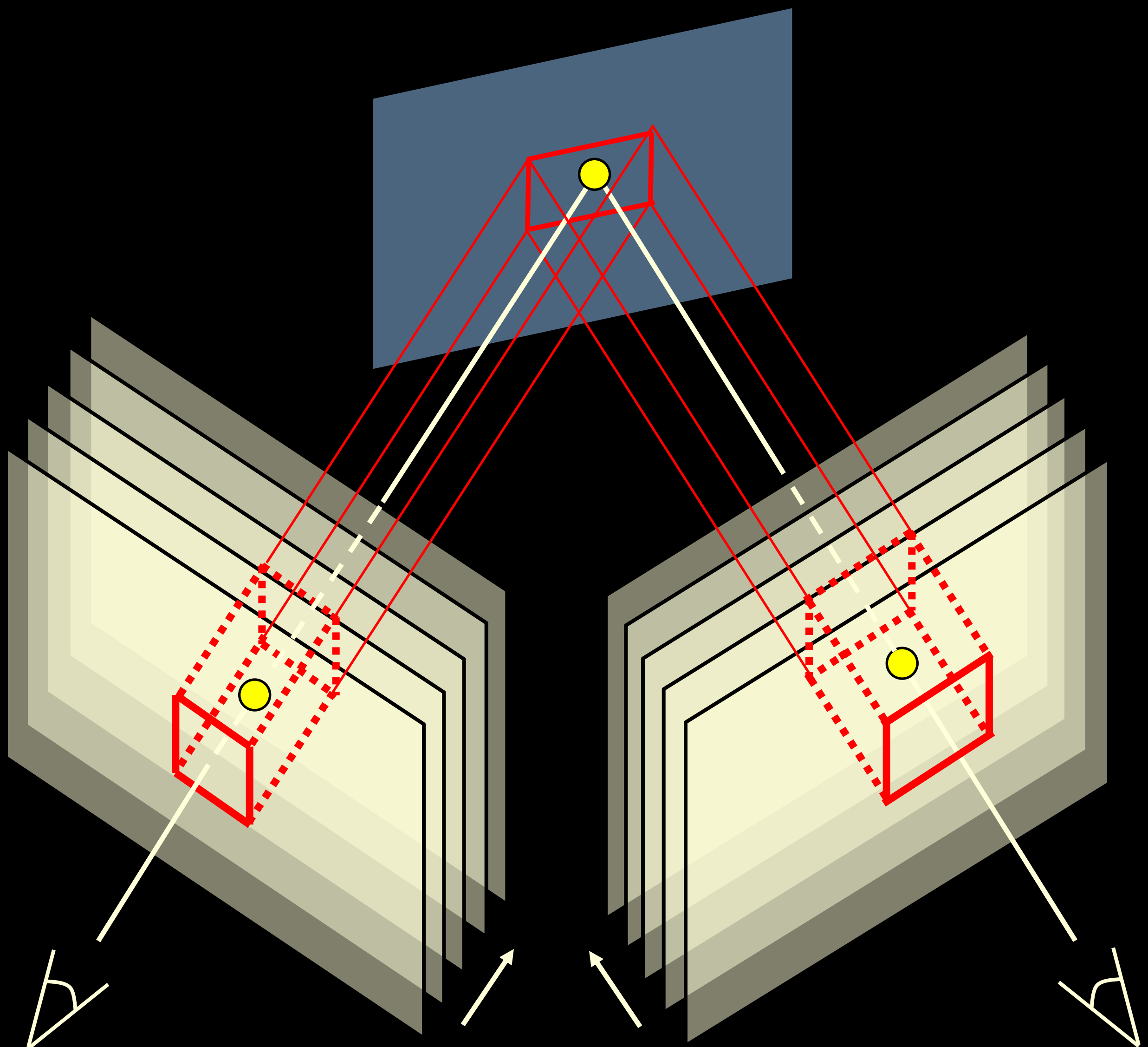
Spacetime Stereo



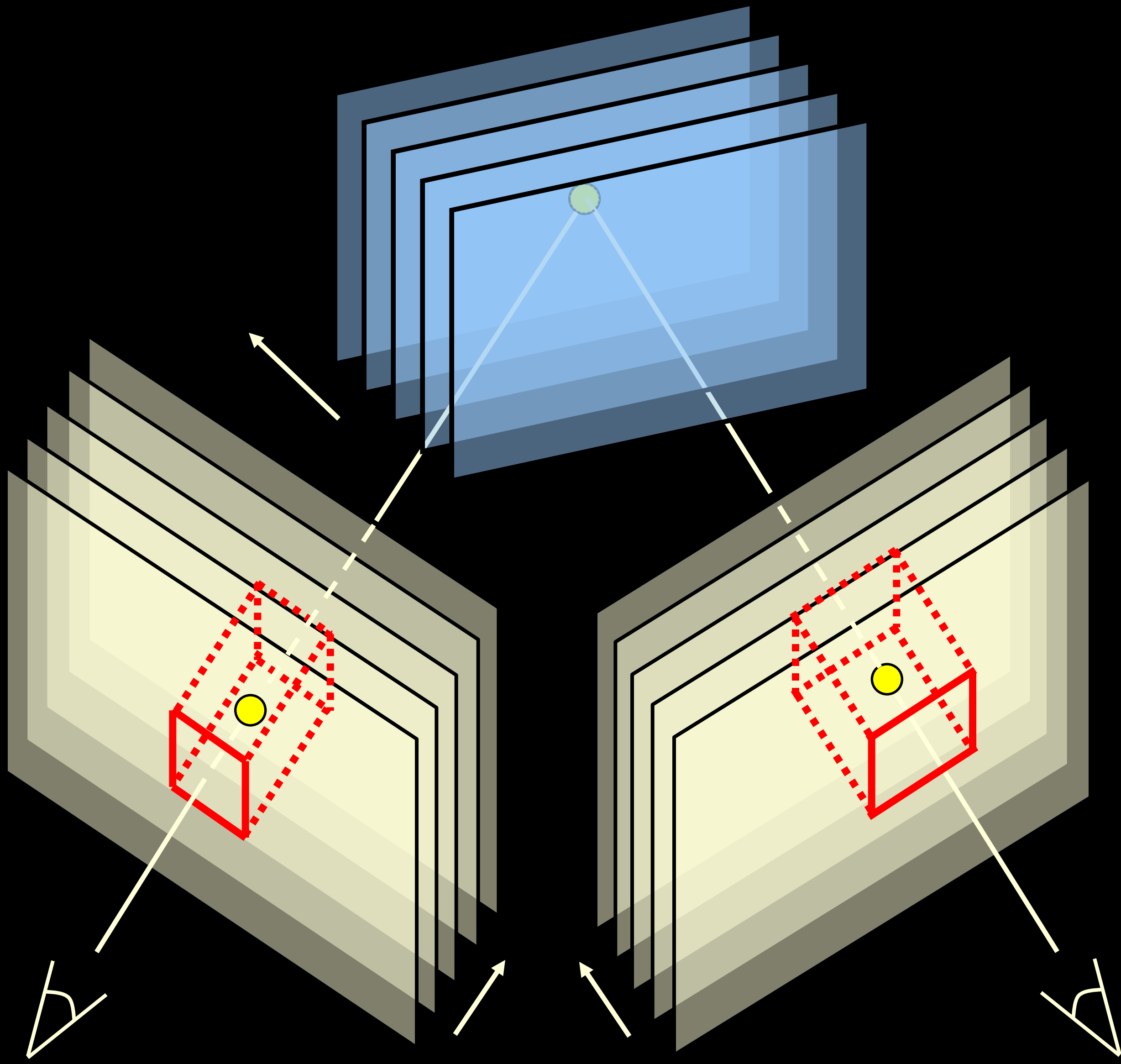
Spacetime Stereo



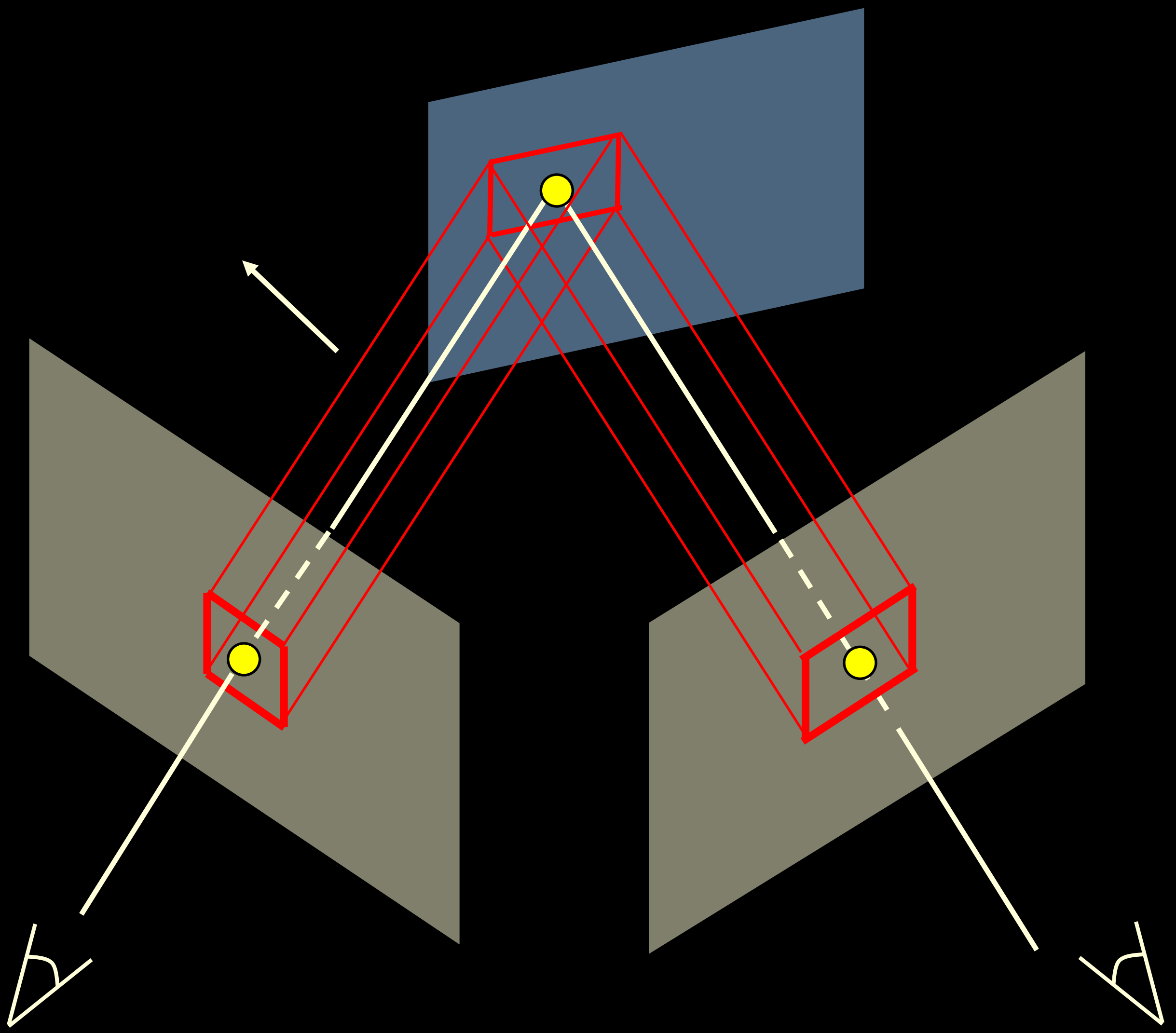
Spacetime Stereo



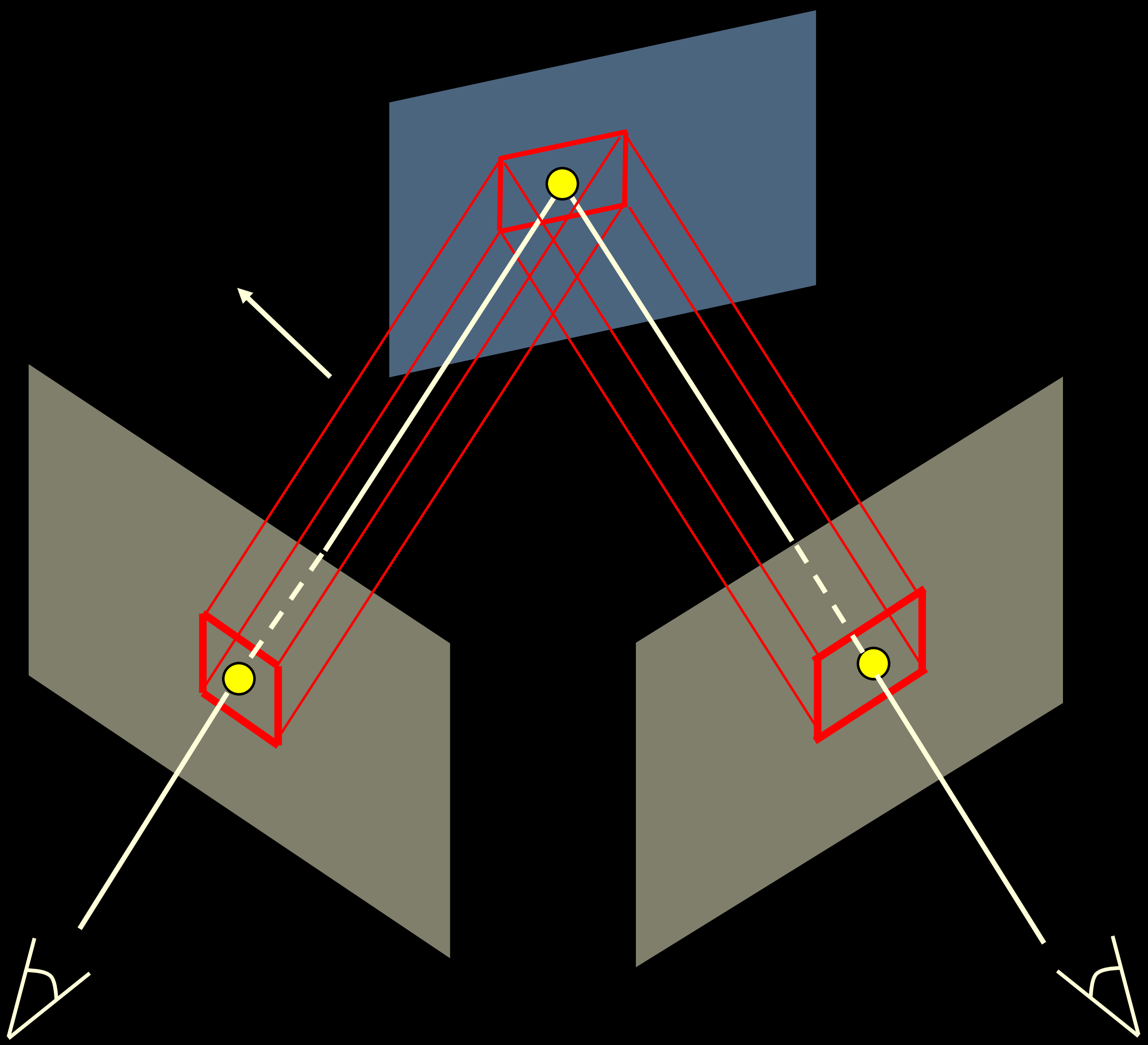
Spacetime Stereo



Spacetime Stereo



Spacetime Stereo



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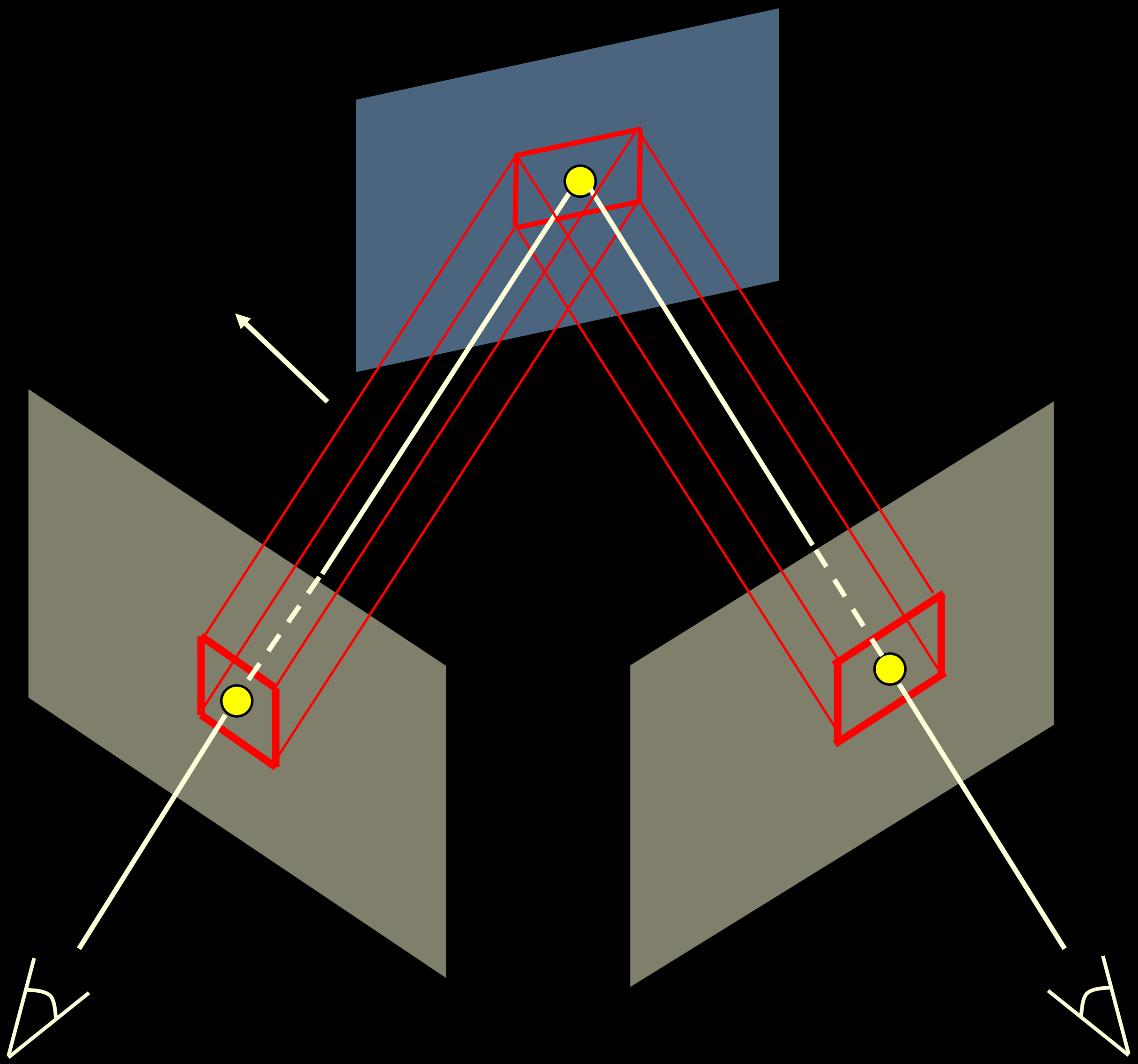

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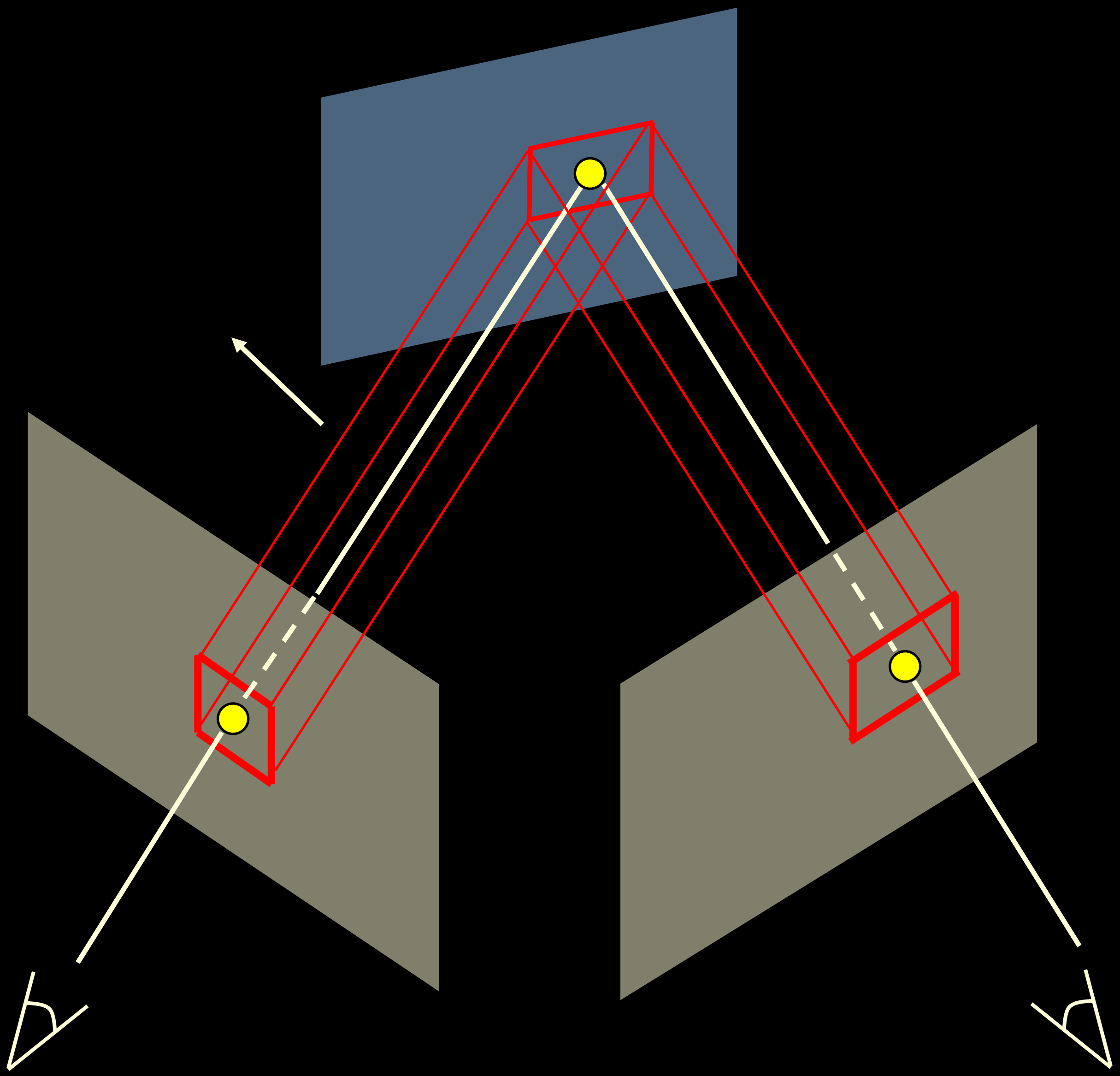
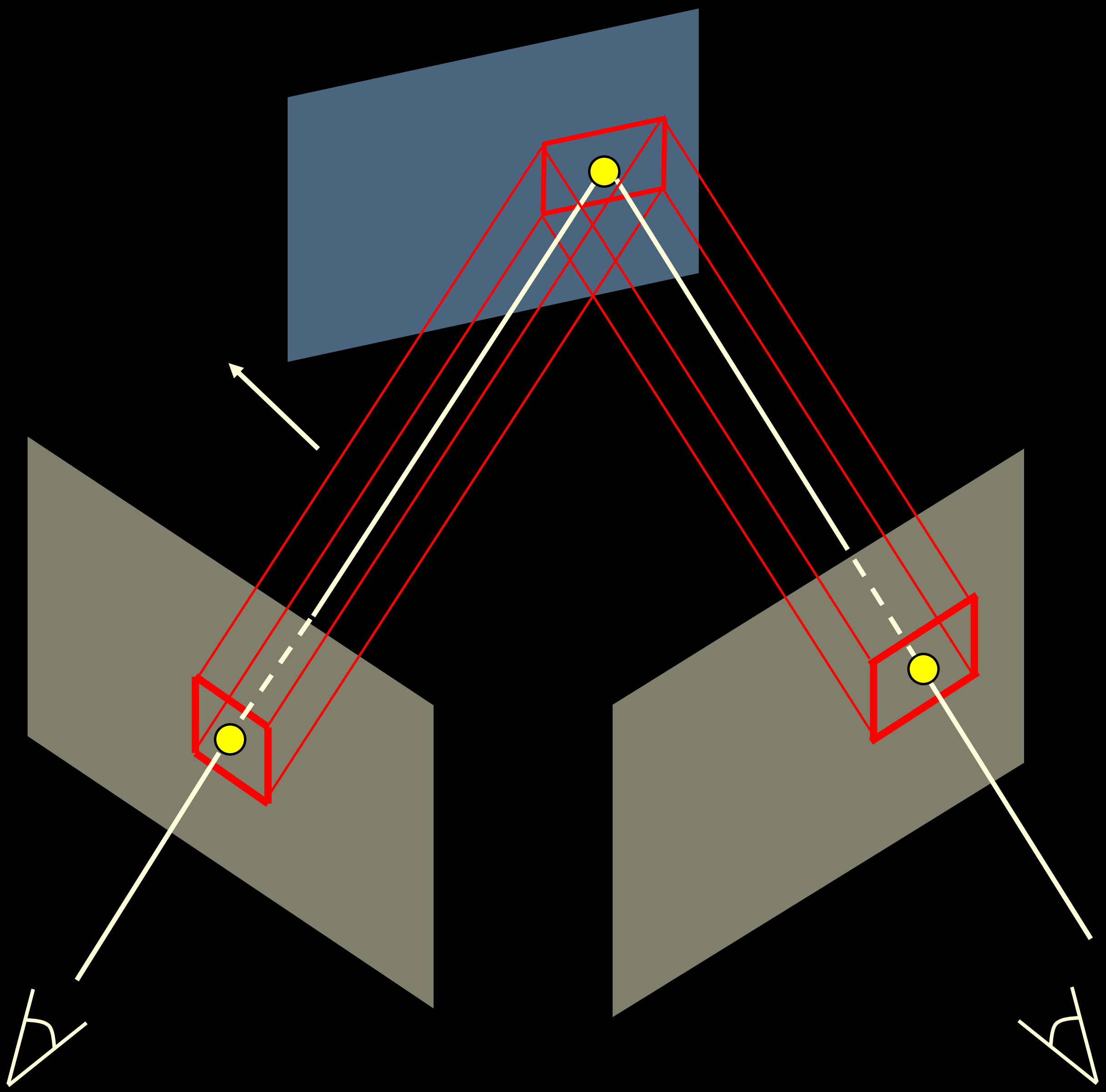
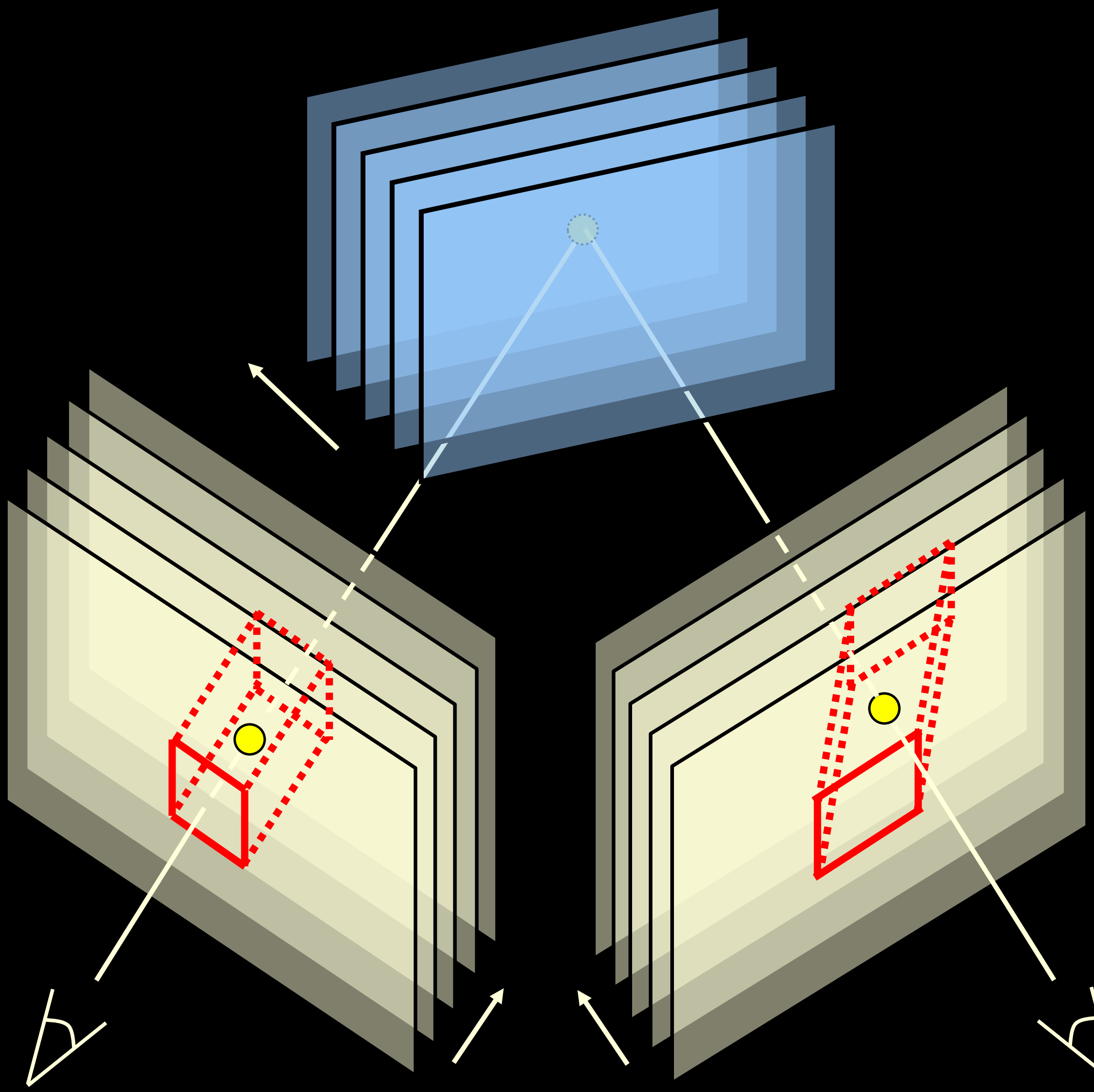


Spacetime Stereo

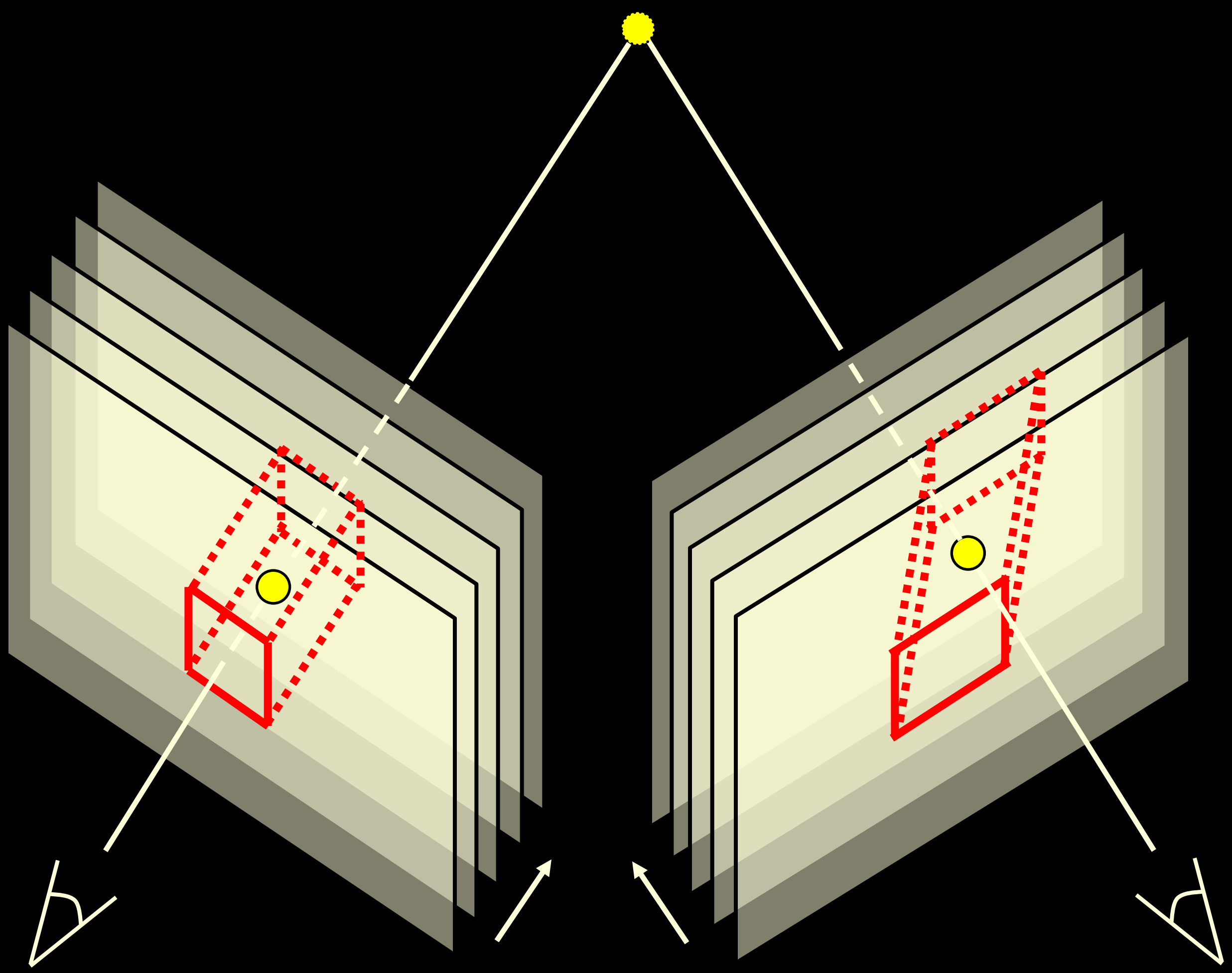


Spacetime Stereo



Spacetime Stereo

Given Videos $Left(x, y, t)$ and $Right(x, y, t)$



Spacetime Stereo

Given Videos $Left(x, y, t)$ and $Right(x, y, t)$

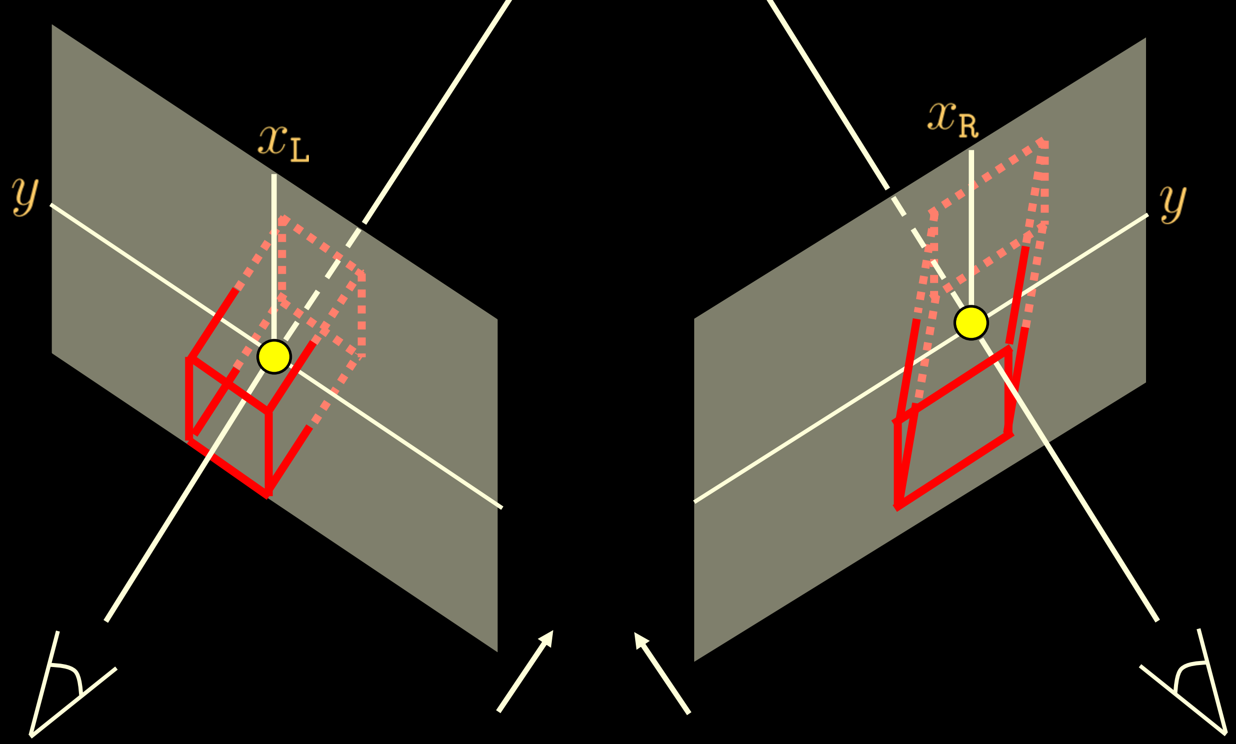
Goal Correspondence $(x_L, y, t) \longrightarrow (x_R, y, t)$

$Disparity \stackrel{\text{def}}{=} x_L - x_R$

Assumption Locally Linear Disparity Model

$\Downarrow$

Affine Volume Deformation: $\{Disparity, Stretch, Shear\}$



Spacetime Stereo

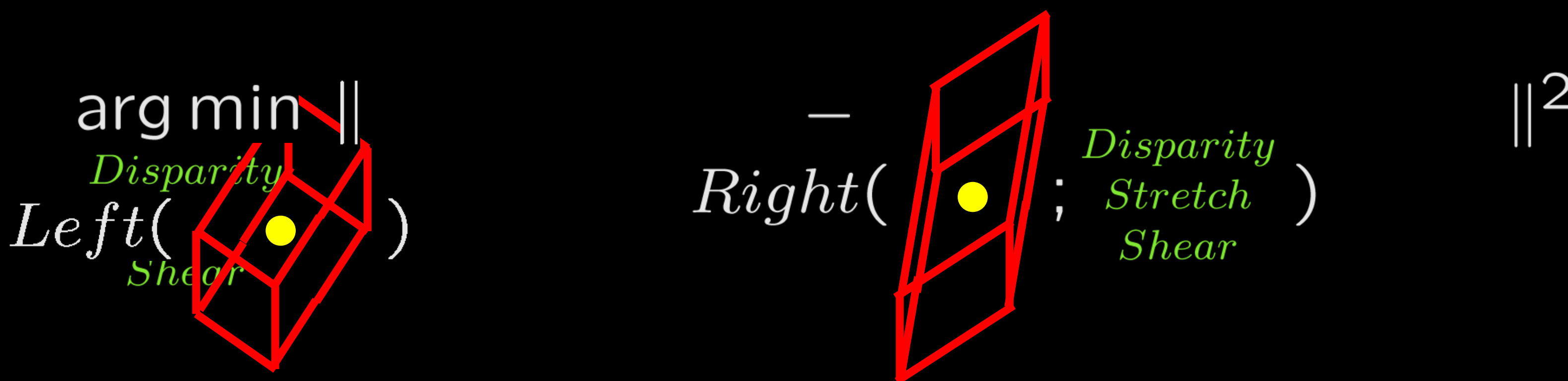
Given Videos $Left(x, y, t)$ and $Right(x, y, t)$

Goal $Disparity \stackrel{\text{def}}{=} x_{\mathrm{L}} - x_{\mathrm{R}}$

Assumption Locally Linear Disparity Model

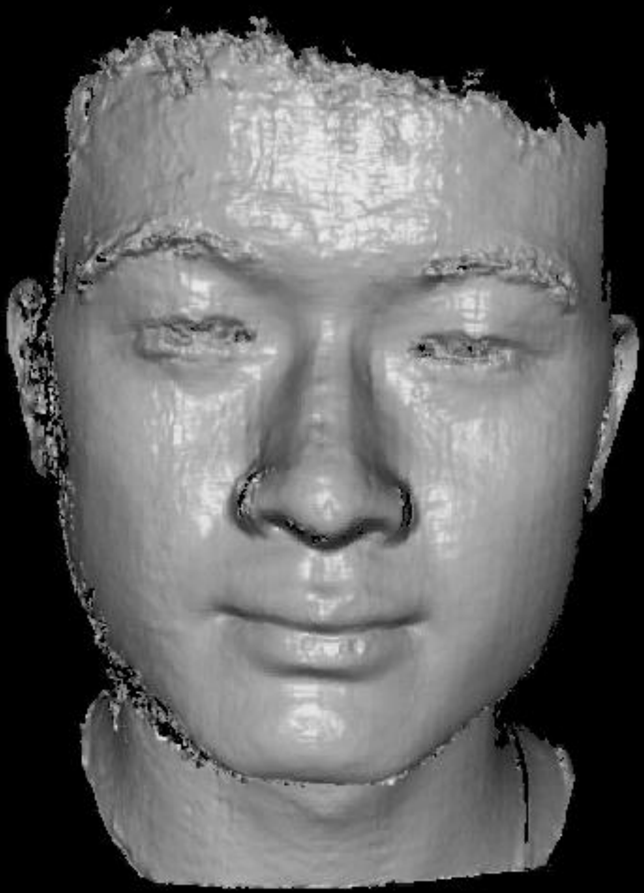
$\Downarrow$

Affine Volume Deformation: $\{Disparity, Stretch, Shear\}$

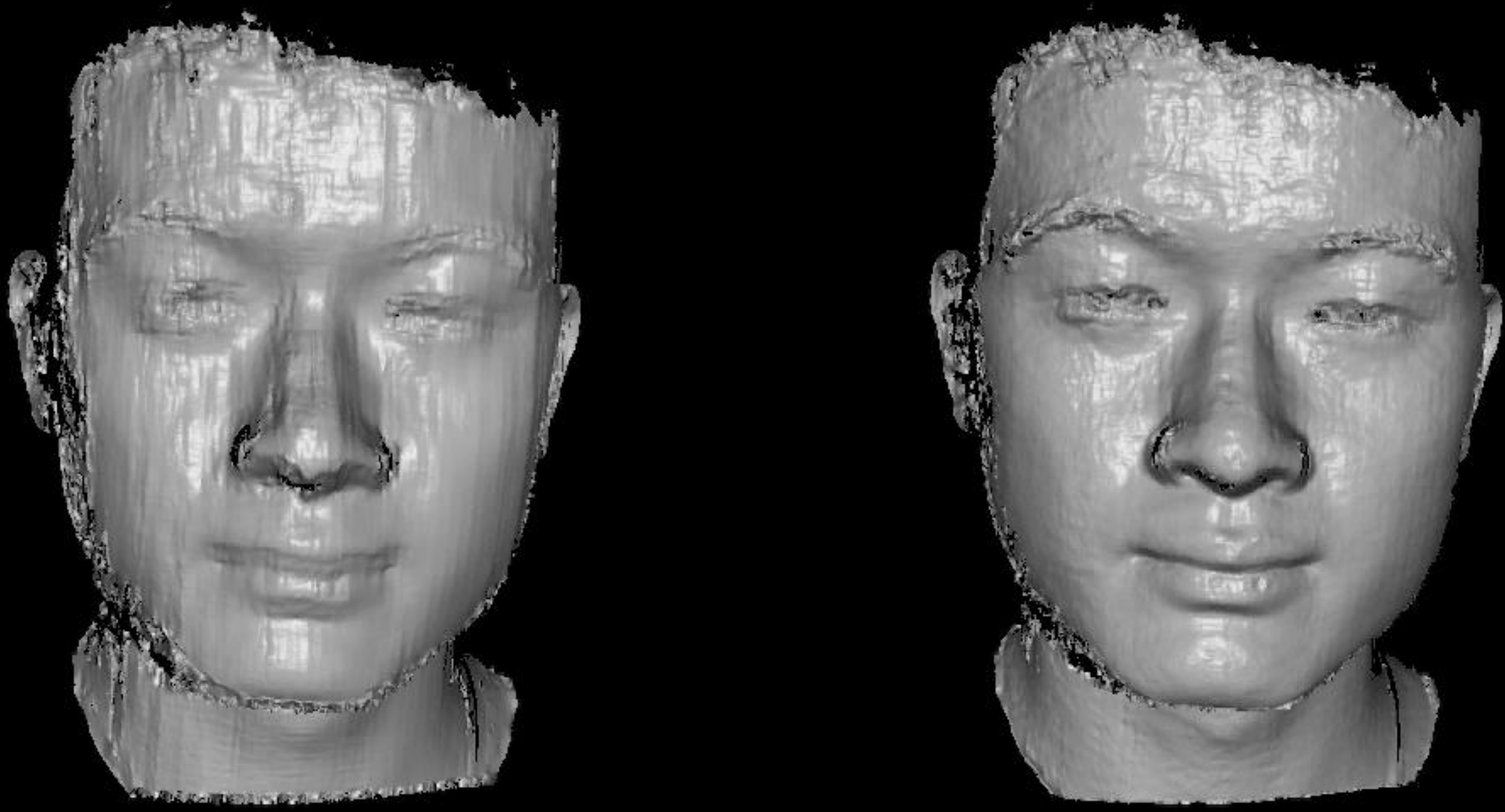


Gauss-Newton Solution, [Zhang *et al.* CVPR2003]
[Davis *et al.* CVPR2003]

Spacetime Stereo

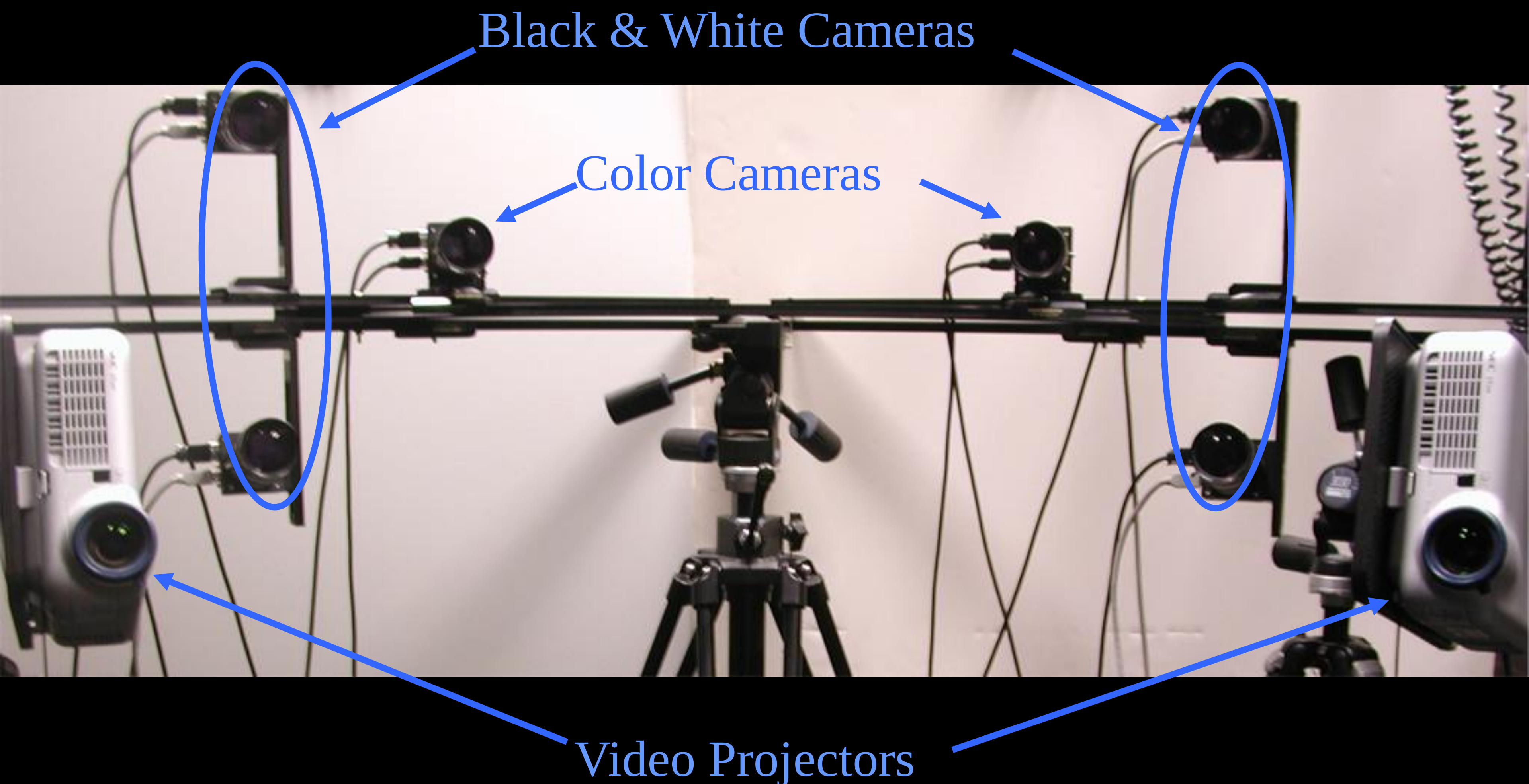


Frame-by-Frame vs. Spacetime Stereo



Spatially More Accurate
Temporally More Stable

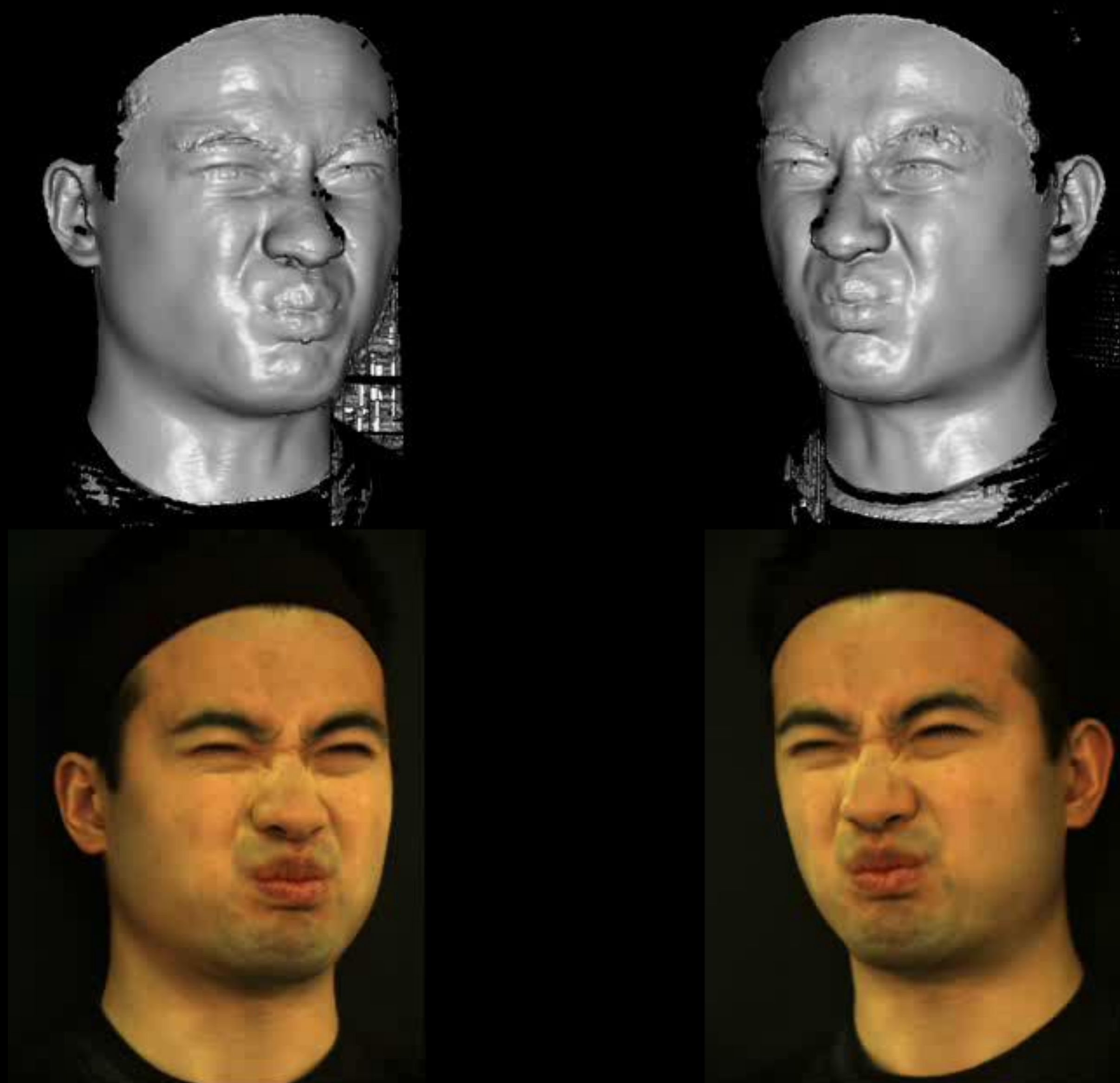
Spacetime Face Capture System



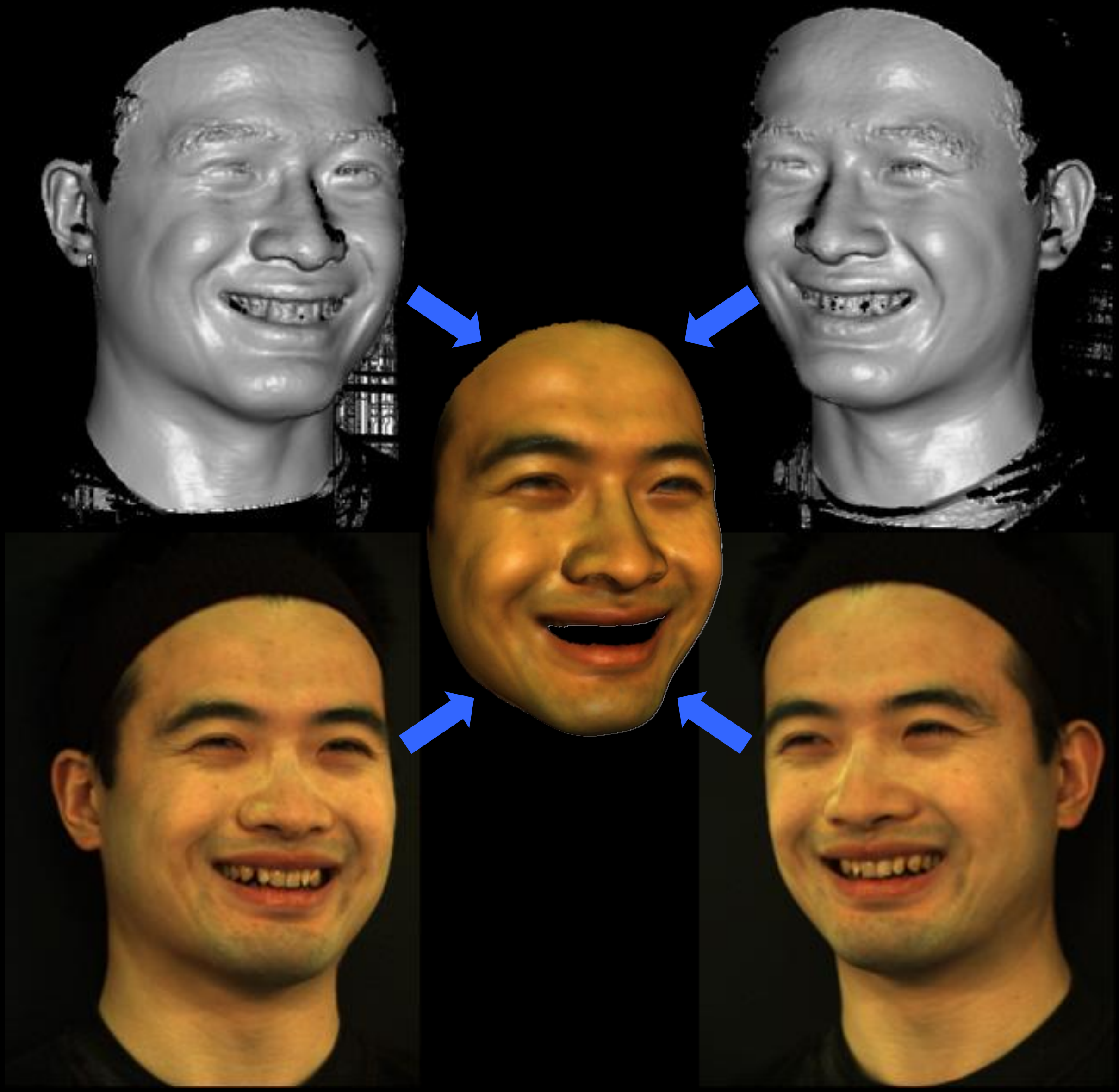
System in Action

Input Videos (640×480, 60fps)

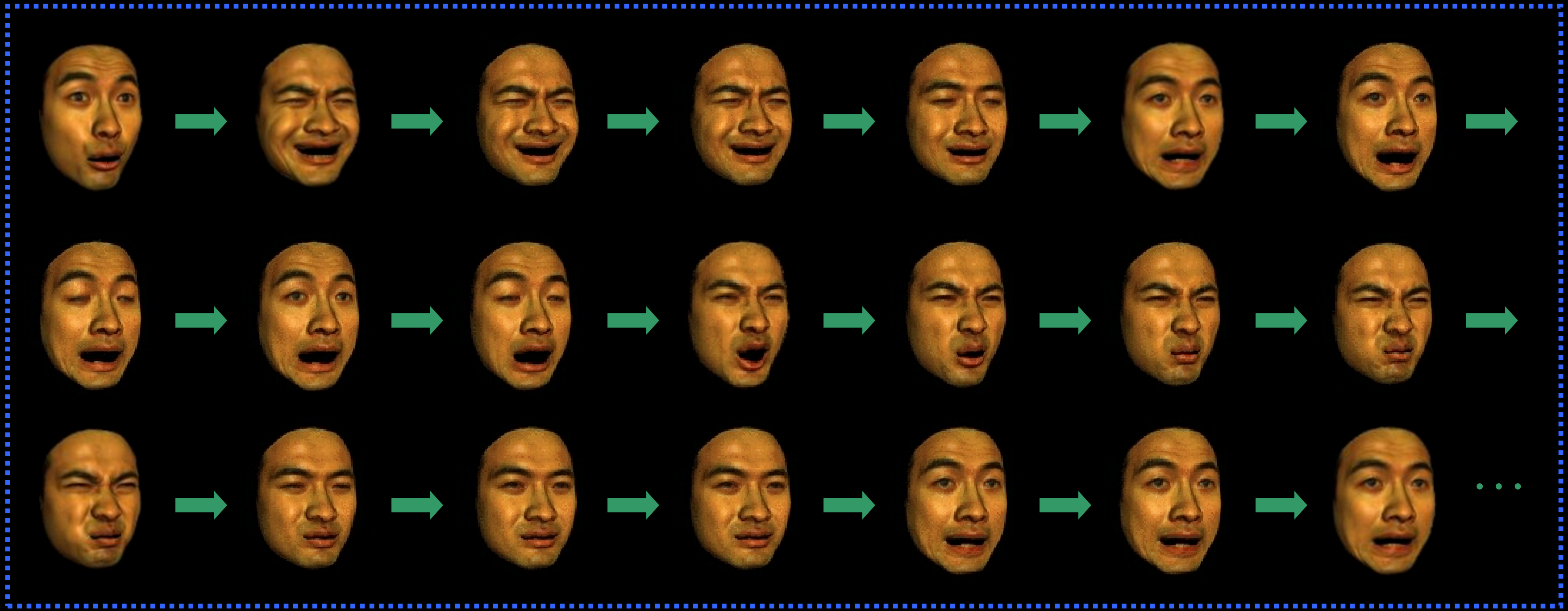
Spacetime Stereo Reconstruction



Creating a Face Database

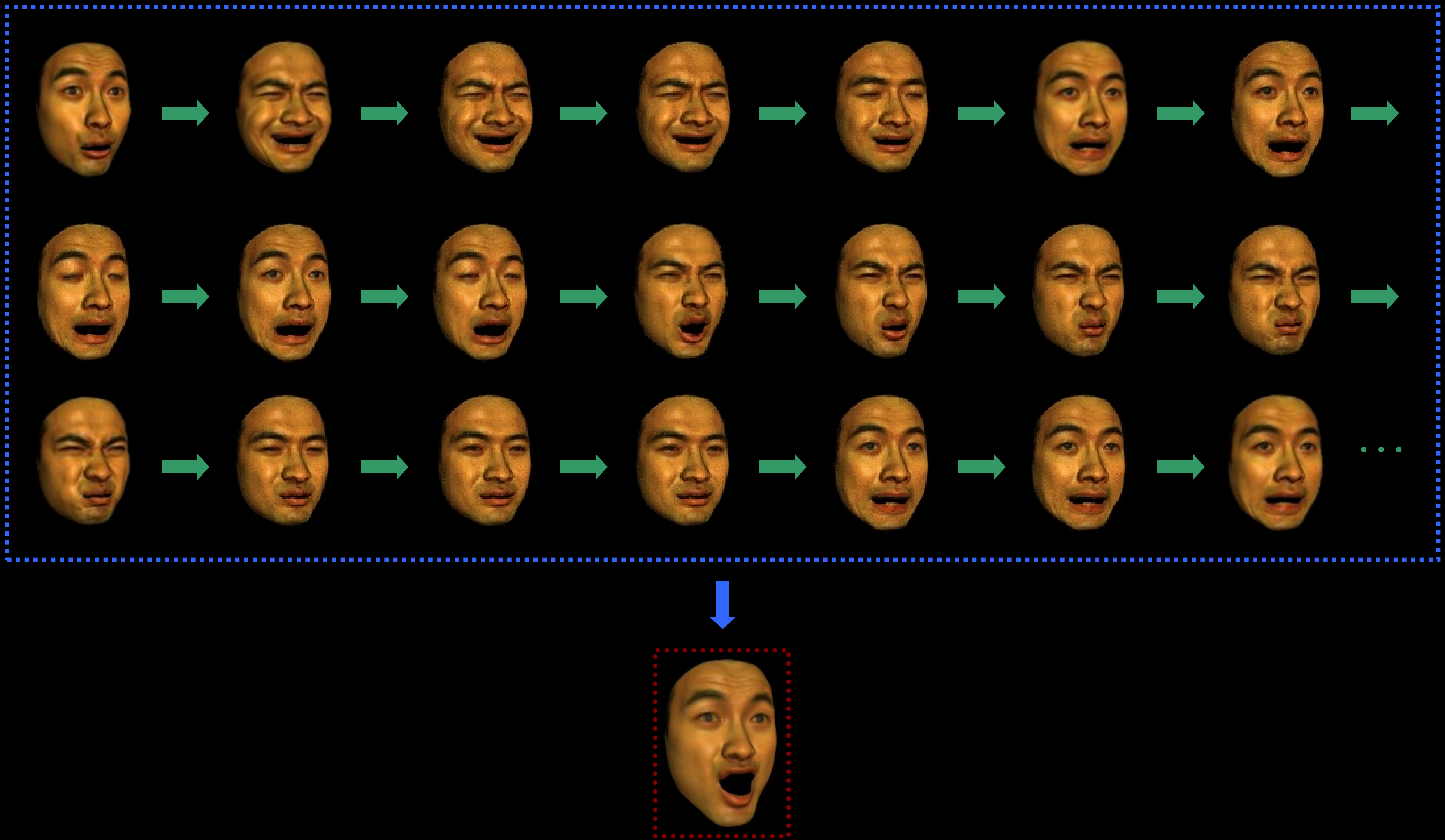


Creating a Face Database



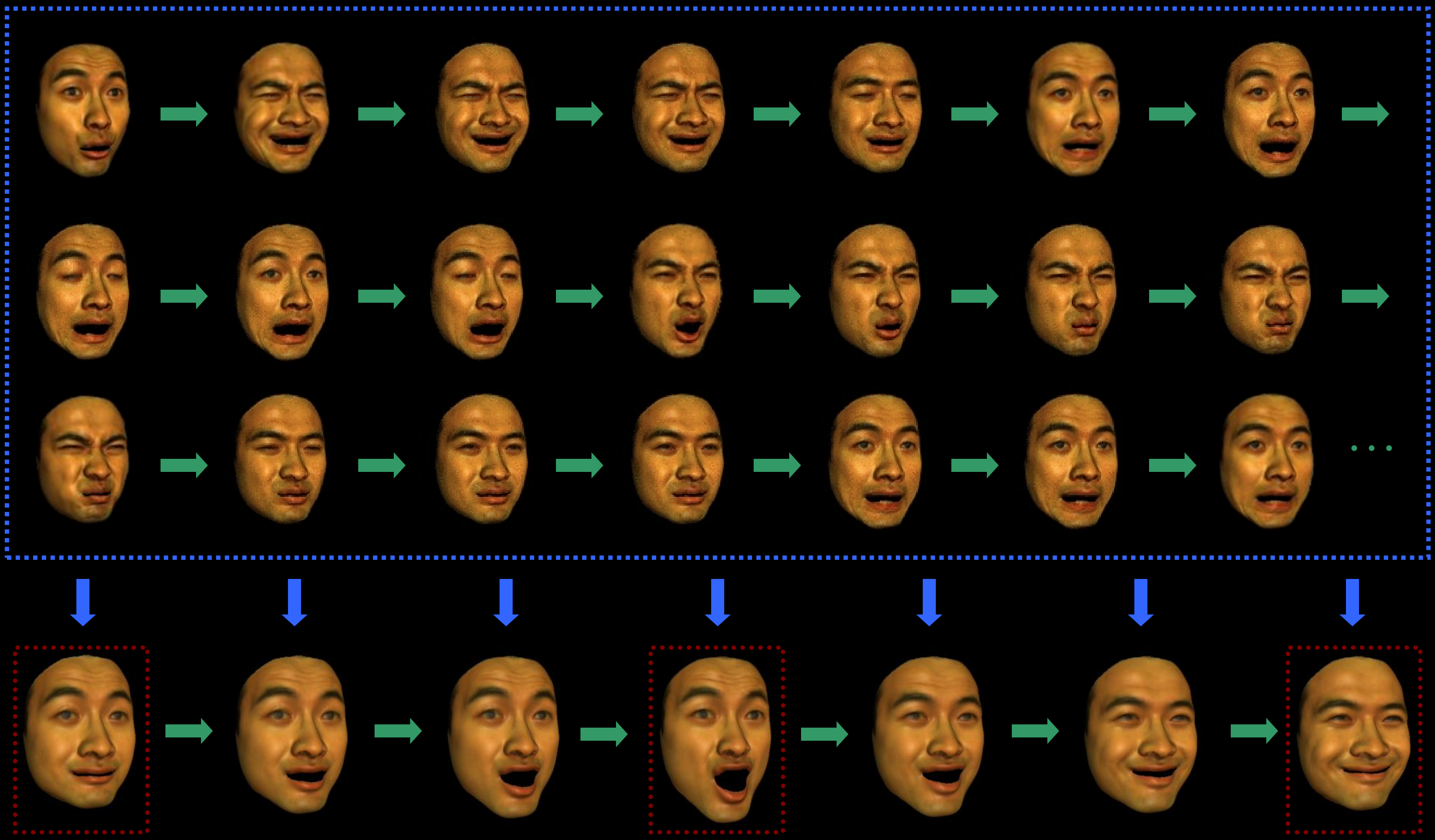
[Zhang *et al.* SIGGRAPH’04]

Application 1: Expression Synthesis



[Zhang *et al.* SIGGRAPH'04]

Application 2: Facial Animation



[Zhang *et al.* SIGGRAPH'04]

Keyframe Animation