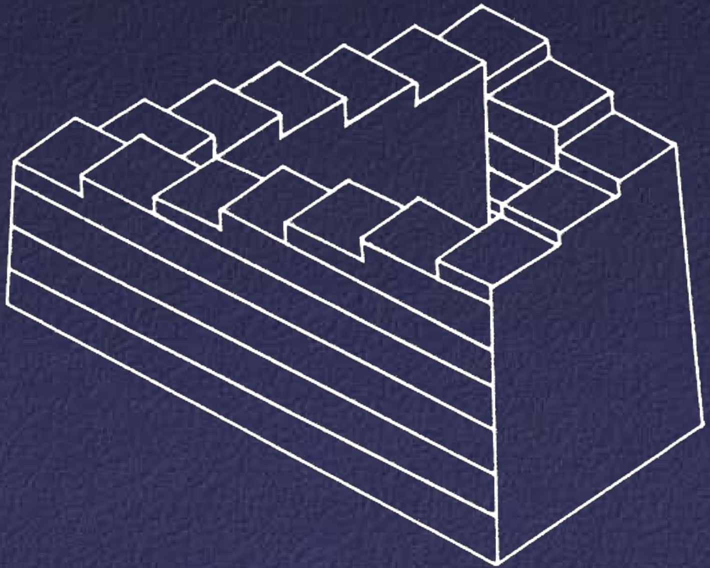
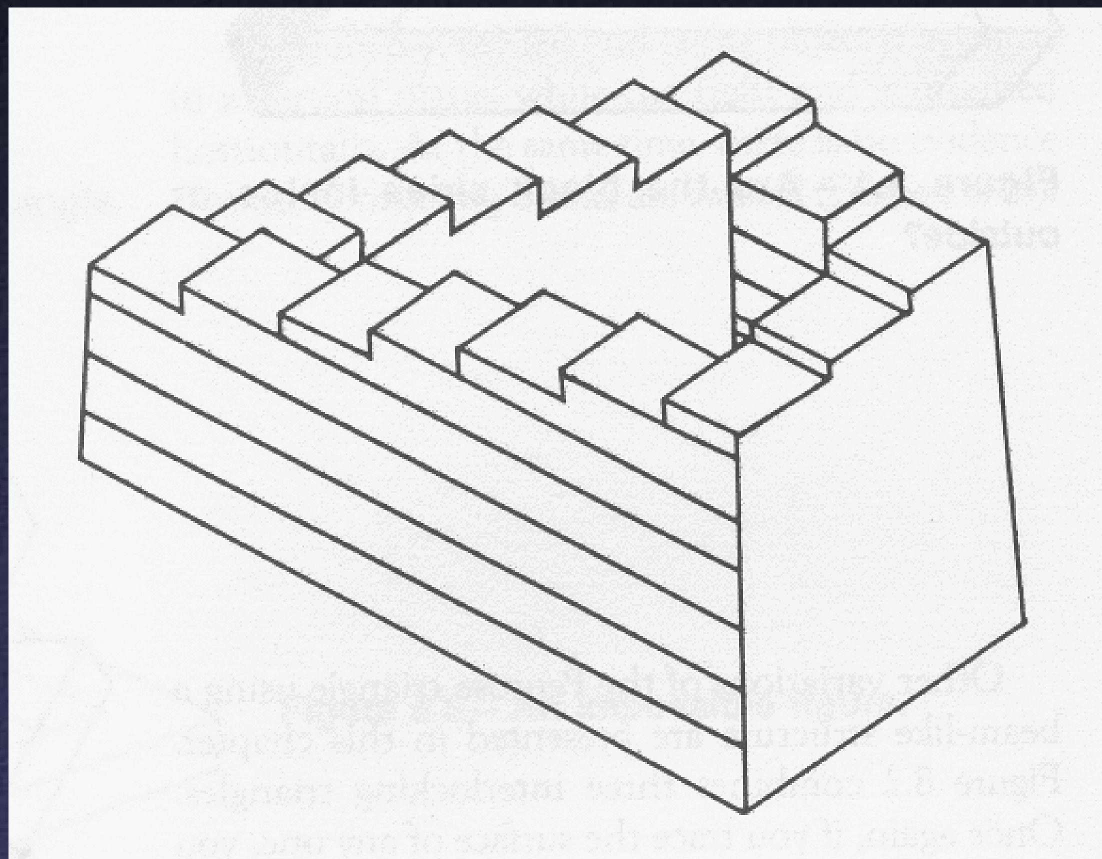
3D Vision

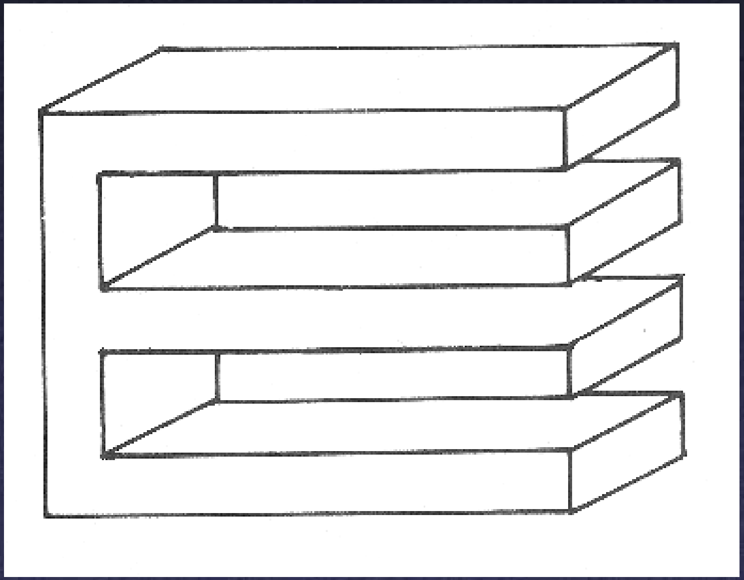


3D Perception: Illusions



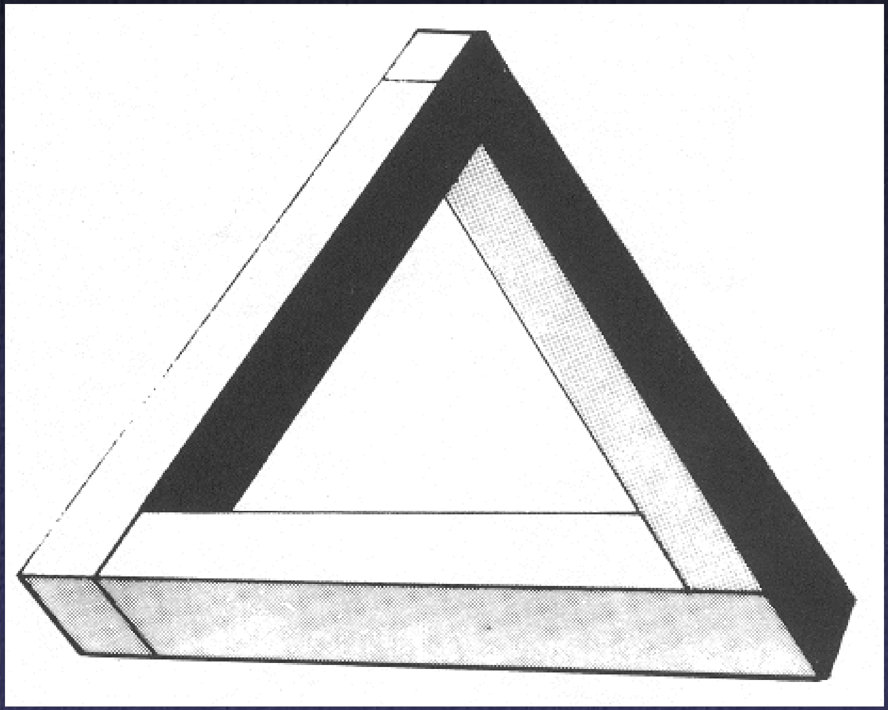
Block & Yuker

3D Perception: Illusions



Block & Yuker

3D Perception: Illusions



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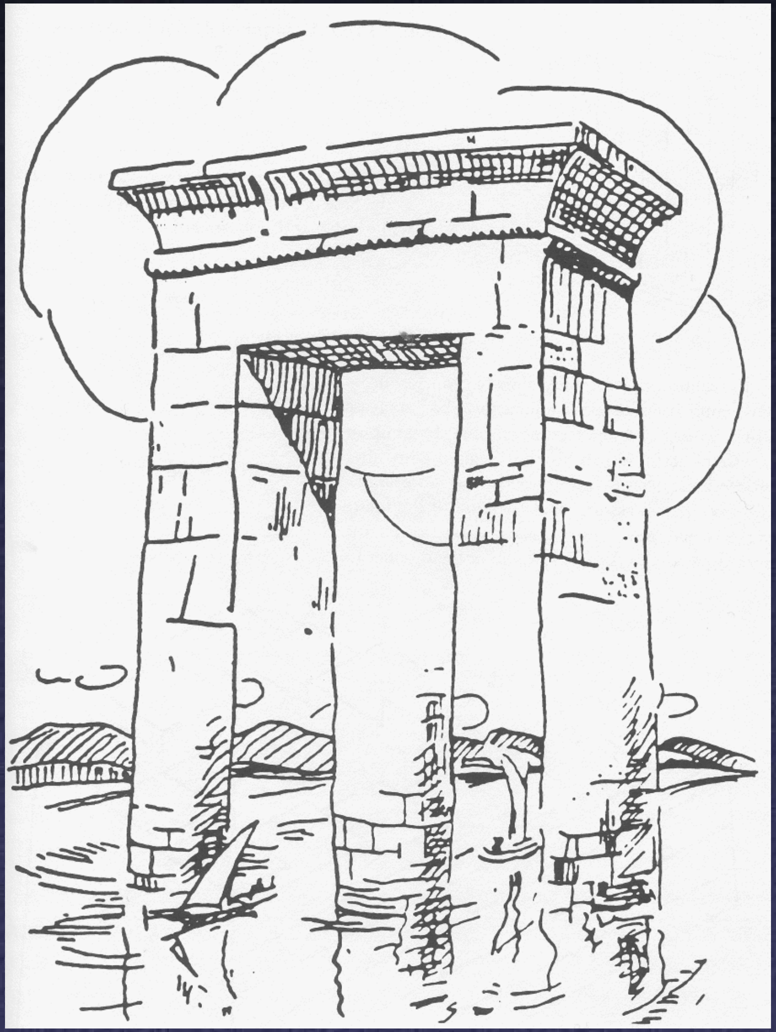
3D Perception: Illusions



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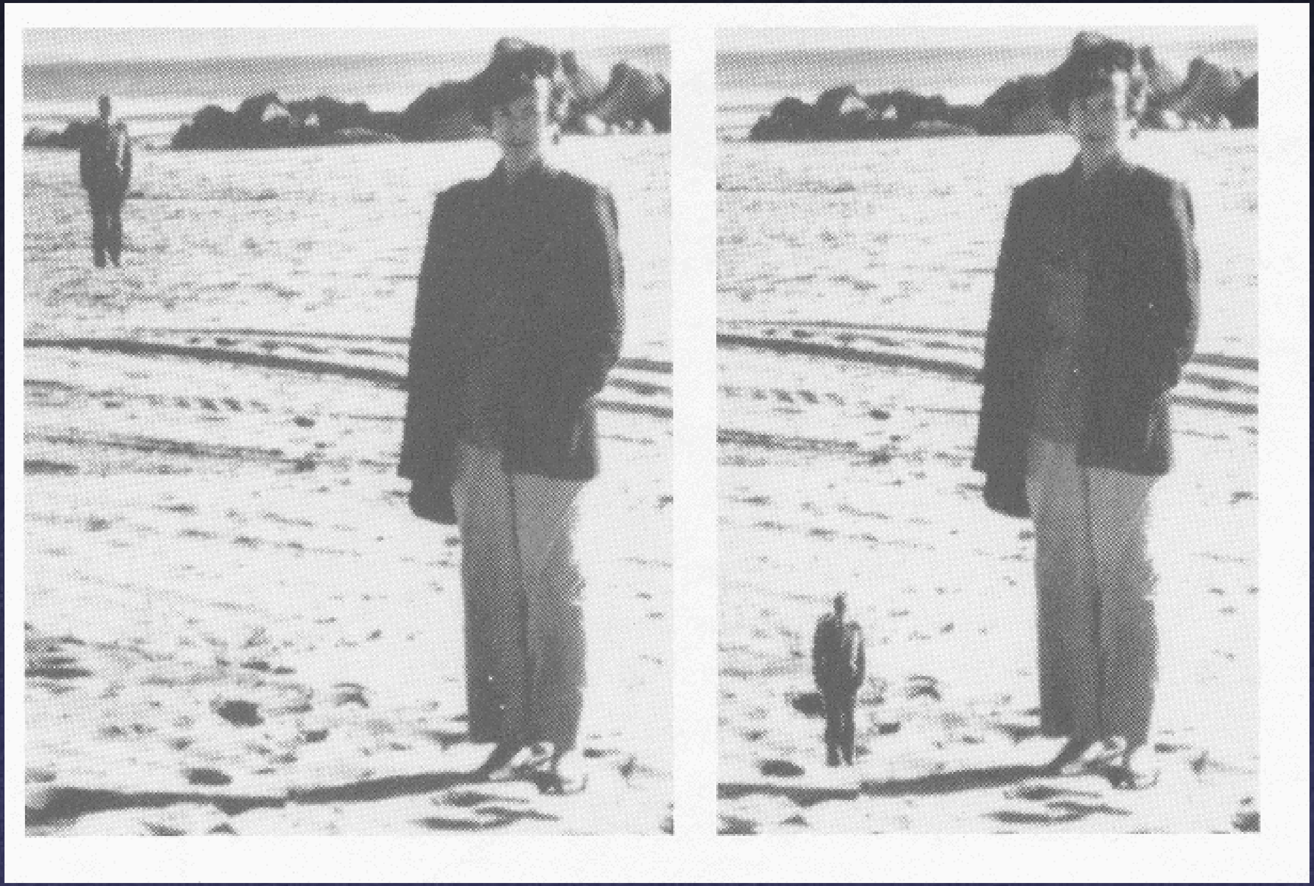
3D Perception: Illusions



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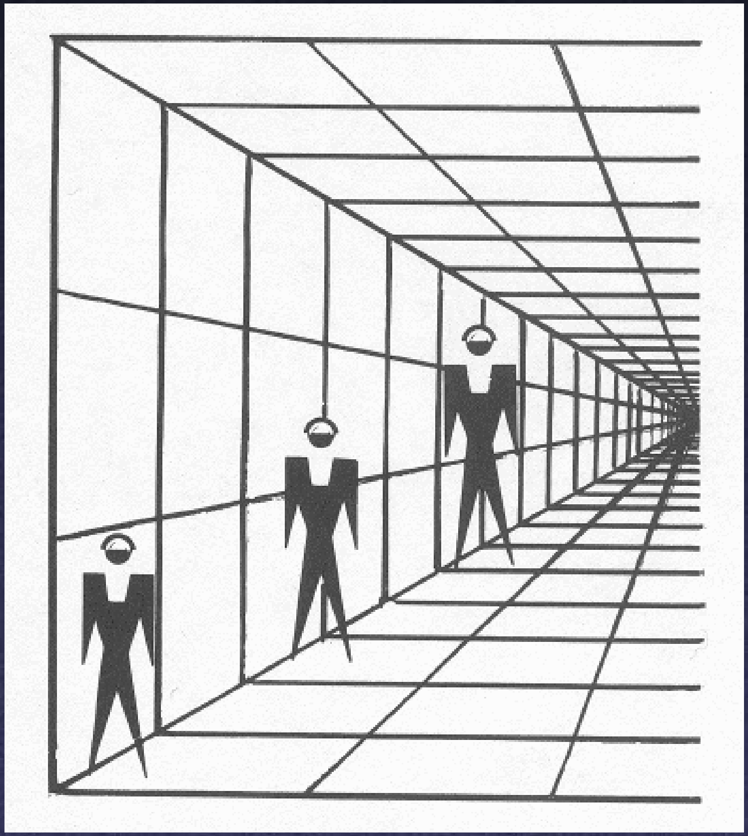
3D Perception: Illusions



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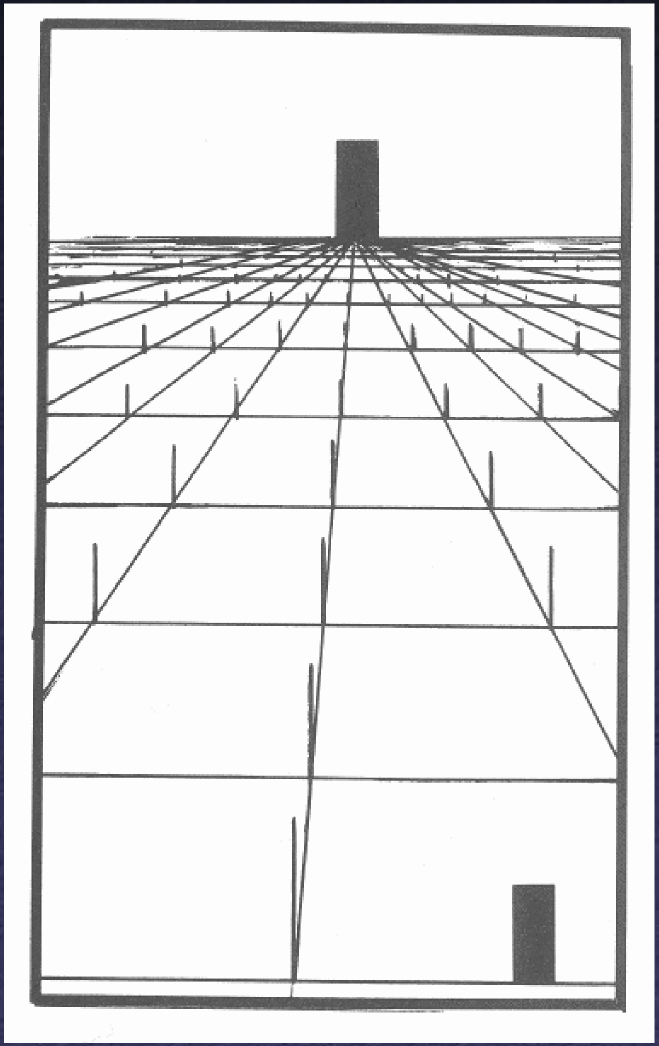
3D Perception: Illusions



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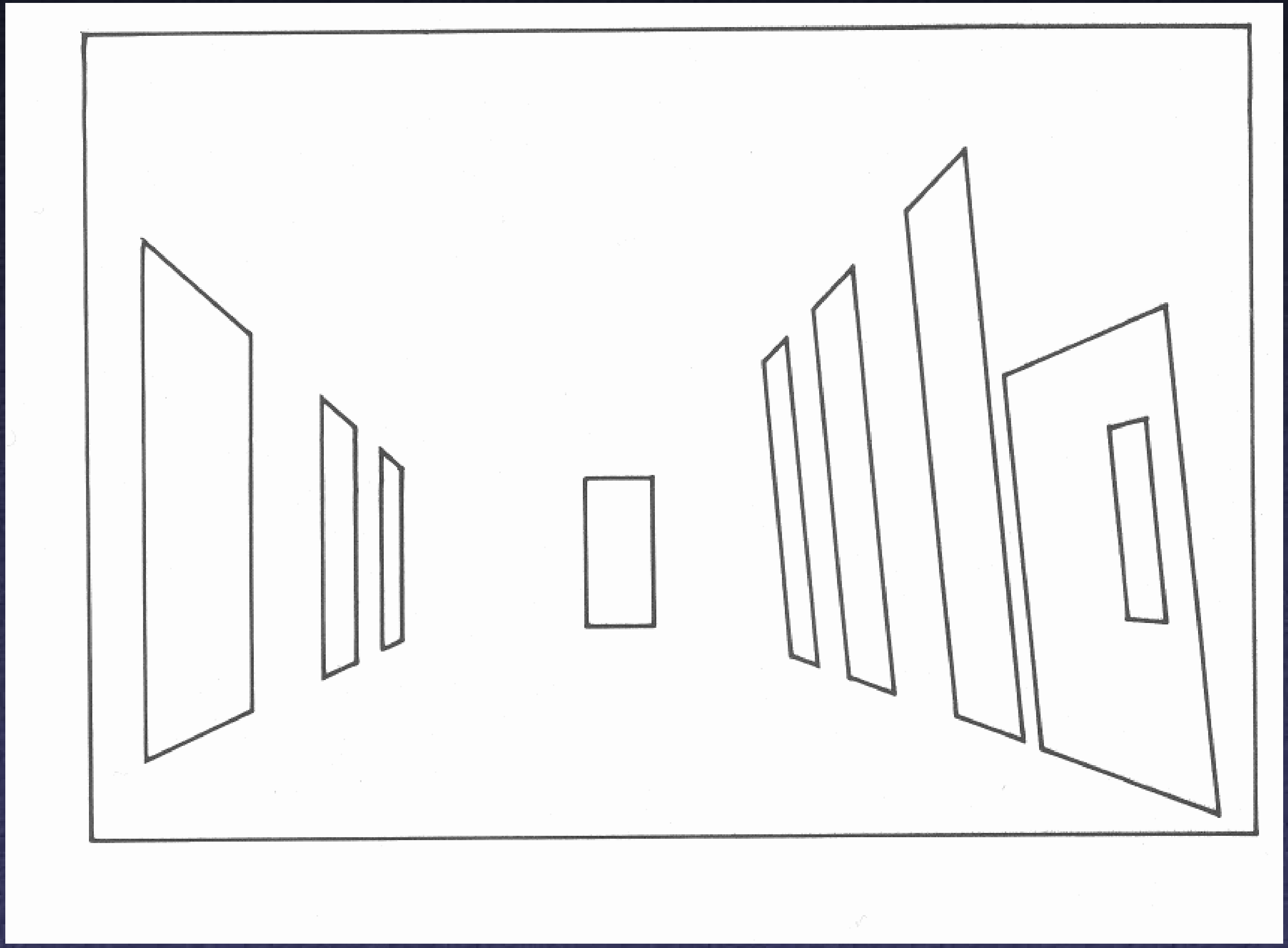
3D Perception: Illusions



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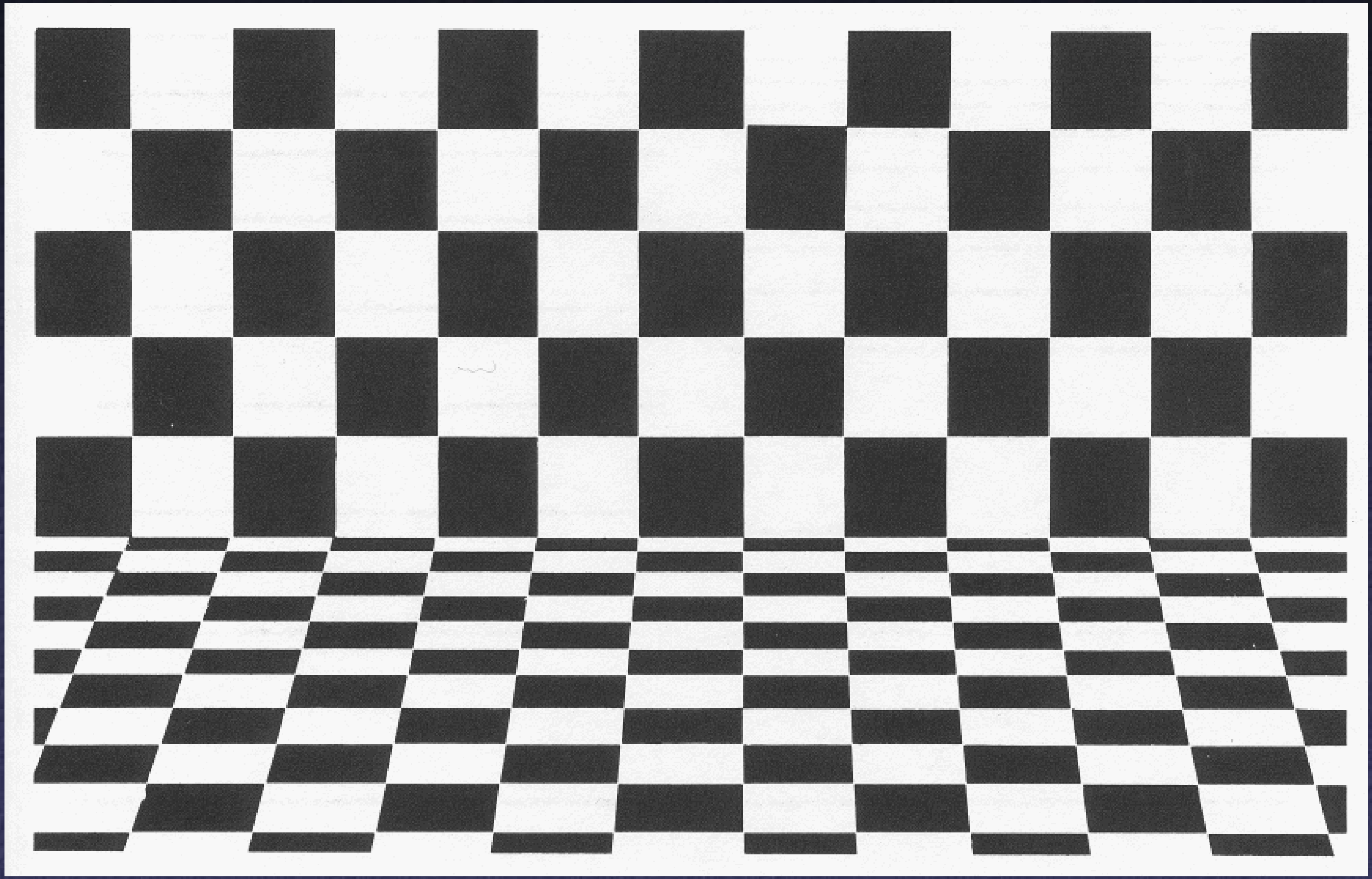
3D Perception: Illusions



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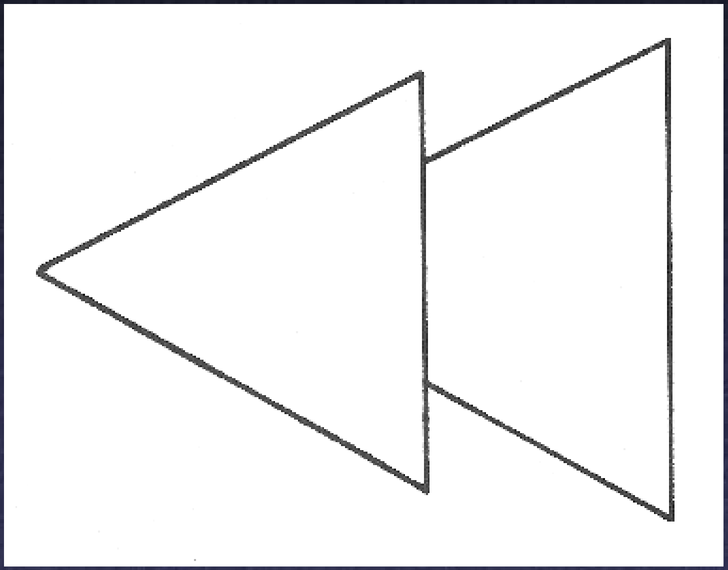
3D Perception: Illusions



Block & Yuker

3D Perception: Conclusions

- Perspective is assumed
- Relative depth ordering
- Occlusion is important
- Local consistency

3D Perception: Stereo

- Experiments show that absolute depth estimation not very accurate
  - Low “relief” judged to be deeper than it is
- Relative depth estimation very accurate
  - Can judge which object is closer for stereo disparities of a few seconds of arc

3D Computer Vision

- Accurate (or not) shape reconstruction
- Some things easier to understand on 3D models than in 2D:
  - Occlusion
  - Variation with lighting (shading)
  - Variation with viewpoint
- As a result, some problems become easier:
  - Segmentation
  - Recognition

3D Data Types

- Point Data
- Volumetric Data
- Surface Data

3D Data Types: Point Data

- “Point clouds”
- Advantage: simplest data type
- Disadvantage: no information on adjacency / connectivity

3D Data Types: Volumetric Data

- Regularly-spaced grid in (x,y,z): “voxels”
- For each grid cell, store
  - Occupancy (binary: occupied / empty)
  - Density
  - Other properties
- Popular in medical imaging
  - CAT scans
  - MRI

3D Data Types: Volumetric Data

- Advantages:
  - Can represent inside of object
  - Uniform sampling: simpler algorithms
- Disadvantages:
  - Lots of data
  - Wastes space if only storing a surface
  - Most “vision” sensors / algorithms return point or surface data

3D Data Types: Surface Data

- Polyhedral
  - Piecewise planar
  - Polygons connected together
  - Most popular: “triangle meshes”
- Smooth
  - Higher-order (quadratic, cubic, etc.) curves
  - Bézier patches, splines, NURBS, subdivision surfaces, etc.

3D Data Types: Surface Data

- Advantages:
  - Usually corresponds to what we see
  - Usually returned by vision sensors / algorithms
- Disadvantages:
  - How to find “surface” for translucent objects?
  - Parameterization often non-uniform
  - Non-topology-preserving algorithms difficult

3D Data Types: Surface Data

- Implicit surfaces (cf. parametric)
  - Zero set of a 3D function
  - Usually regularly sampled (voxel grid)
- Advantage: easy to write algorithms that change topology
- Disadvantage: wasted space, time

2½-D Data

- Image: stores an intensity / color along each of a set of regularly-spaced rays in space
- Range image: stores a depth along each of a set of regularly-spaced rays in space
- Not a complete 3D description: does not store objects occluded (from some viewpoint)
- View-dependent scene description

2½-D Data

- This is what most sensors / algorithms really return
- Advantages
  - Uniform parameterization
  - Adjacency / connectivity information
- Disadvantages
  - Does not represent entire object
  - View dependent

2½-D Data

- Range images
- Range surfaces
- Depth images
- Depth maps
- Height fields
- 2½-D images
- Surface profiles
- xyz maps
- …

Range Acquisition Taxonomy

- Range acquisition
  - Contact
    - Mechanical (CMM, jointed arm)
    - Inertial (gyroscope, accelerometer)
    - Ultrasonic trackers
    - Magnetic trackers
  - Transmissive
    - Industrial CT
    - Ultrasound
    - MRI
  - Reflective
    - Non-optical
      - Radar
      - Sonar
    - Optical

Range Acquisition Taxonomy

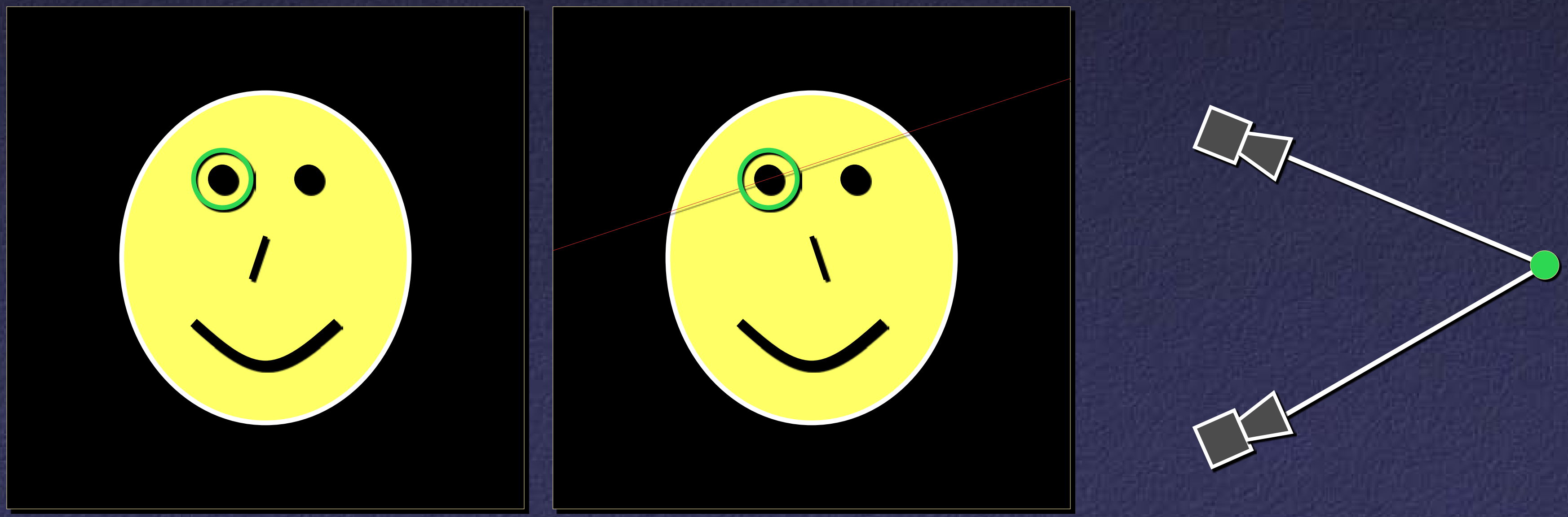
- Optical methods
  - Passive
    - Shape from X:
      - stereo
      - motion
      - shading
      - texture
      - focus
      - defocus
  - Active
    - Active variants of passive methods
      - Stereo w. projected texture
      - Active depth from defocus
      - Photometric stereo
    - Time of flight
    - Triangulation

Optical Range Acquisition Methods

- Advantages:
  - Non-contact
  - Safe
  - Usually inexpensive
  - Usually fast
- Disadvantages:
  - Sensitive to transparency
  - Confused by specularity and interreflection
  - Texture (helps some methods, hurts others)

Stereo

- Find feature in one image, search along epipolar line in other image for correspondence



Stereo

- Advantages:
  - Passive
  - Cheap hardware (2 cameras)
  - Easy to accommodate motion
  - Intuitive analogue to human vision
- Disadvantages:
  - Only acquire good data at "features"
  - Sparse, relatively noisy data (correspondence is hard)
  - Bad around silhouettes
  - Confused by non-diffuse surfaces
- Variant: multibaseline stereo to reduce ambiguity

Shape from Motion

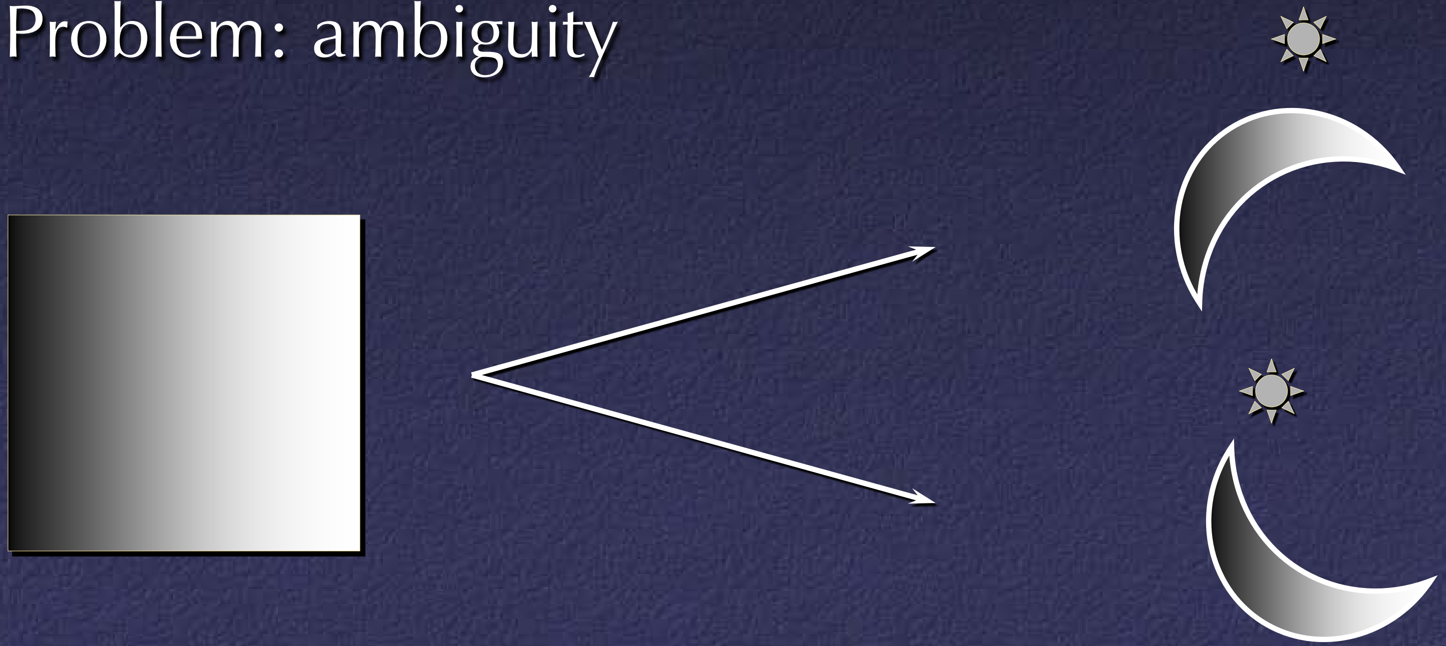
- "Limiting case" of multibaseline stereo
- Track a feature in a video sequence
- For n frames and f features, have $2 \cdot n \cdot f$ knowns, $6 \cdot n + 3 \cdot f$ unknowns

Shape from Motion

- Advantages:
  - Feature tracking easier than correspondence in far-away views
  - Mathematically more stable (large baseline)
- Disadvantages:
  - Does not accommodate object motion
  - Still problems in areas of low texture, in non-diffuse regions, and around silhouettes

Shape from Shading

- Given: image of surface with known, constant reflectance under known point light
- Estimate normals, integrate to find surface
- Problem: ambiguity

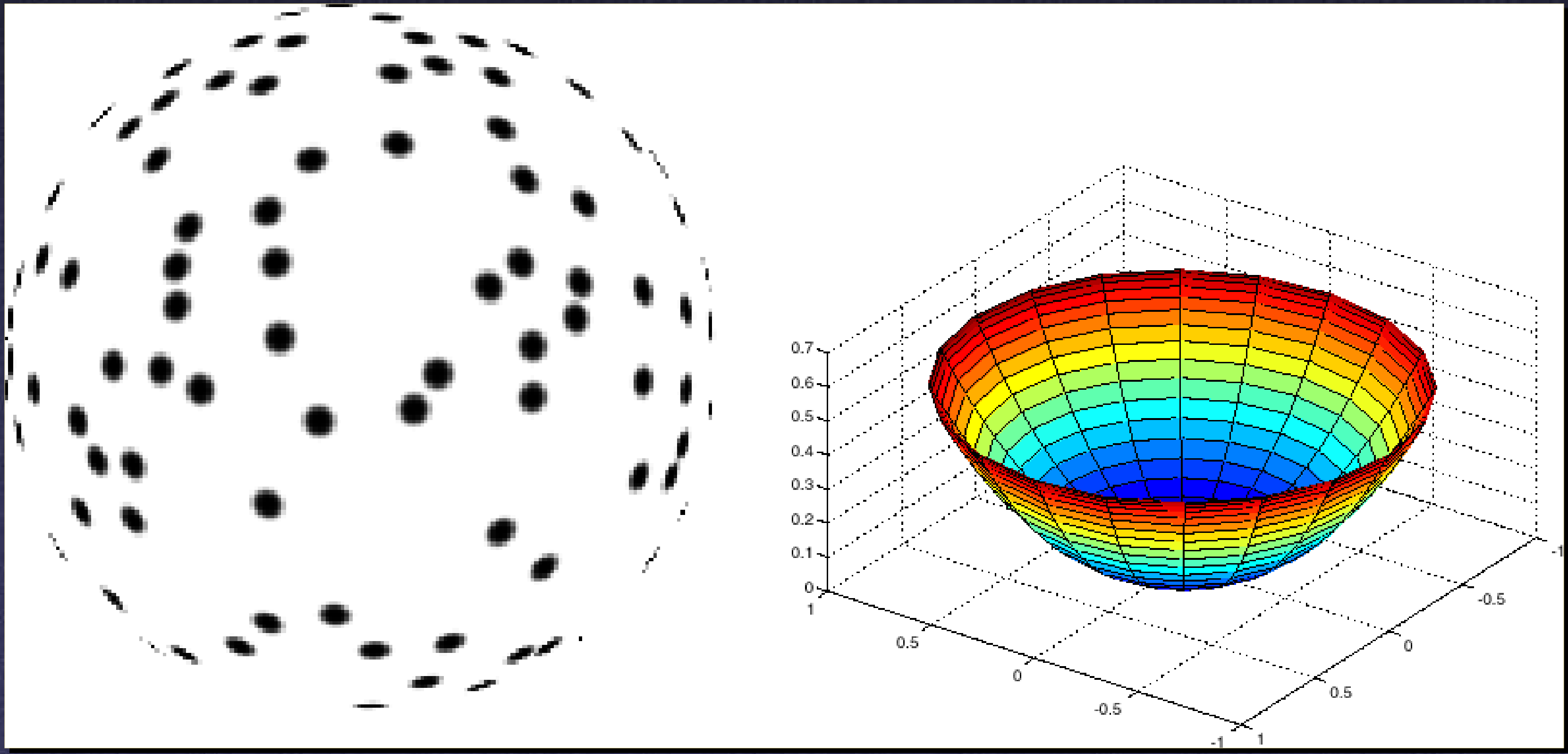


Shape from Shading

- Advantages:
  - Single image
  - No correspondences
  - Analogue in human vision
- Disadvantages:
  - Mathematically unstable
  - Can't have texture
- "Photometric stereo" (active method) more practical than passive version

Shape from Texture

- Mathematically similar to shape from shading, but uses stretch and shrink of a (regular) texture



Shape from Texture

- Analogue to human vision
- Same disadvantages as shape from shading

Shape from Focus and Defocus

- Shape from focus: at which focus setting is a given image region sharpest?
- Shape from defocus: how out-of-focus is each image region?
- Passive versions rarely used
- Active depth from defocus can be made practical

Correspondence and Stereopsis

Original notes by W. Correa. Figures from [Forsyth & Ponce] and [Trucco & Verri]

Introduction

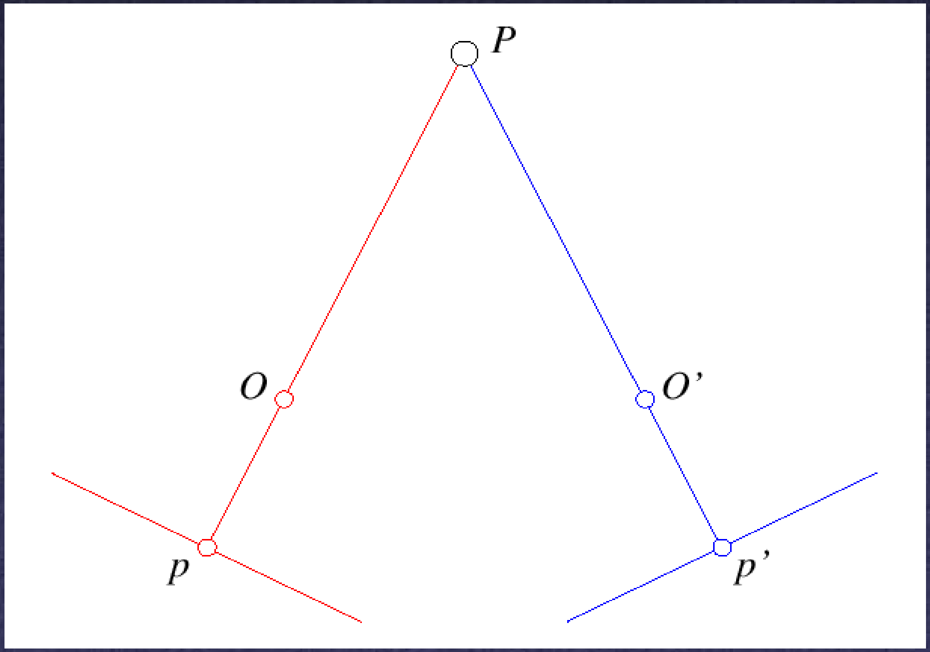
- Disparity:
  - Informally: difference between two pictures
  - Allows us to gain a strong sense of depth
- Stereopsis:
  - Ability to perceive depth from disparity
- Goal:
  - Design algorithms that mimic stereopsis

Stereo Vision

- Two parts
  - Binocular fusion of features observed by the eyes
  - Reconstruction of their three-dimensional preimage

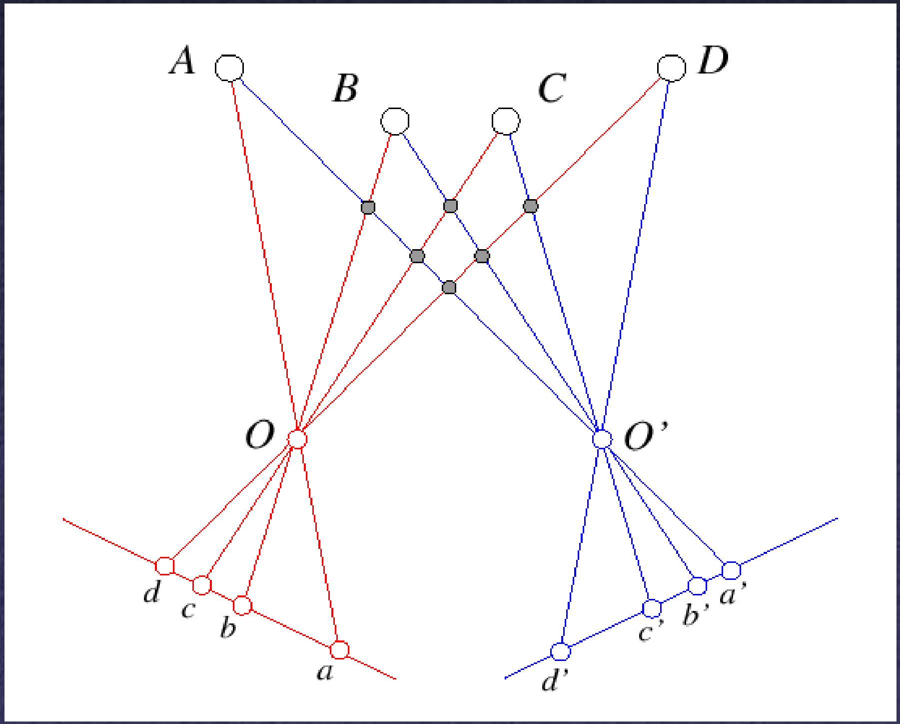
Stereo Vision – Easy Case

- A single point being observed
  - The preimage can be found at the intersection of the rays from the focal points to the image points



Stereo Vision – Hard Case

- Many points being observed
  - Need some method to establish correspondences



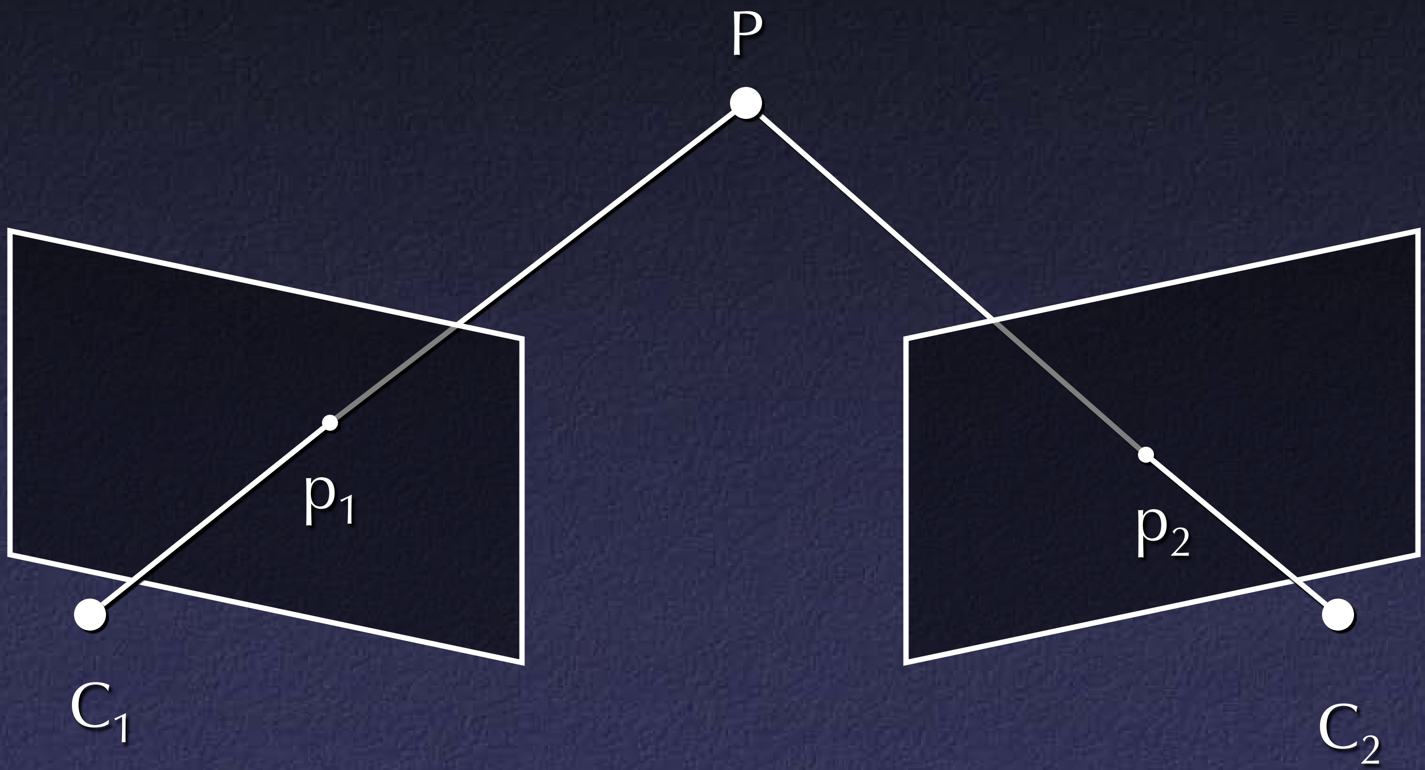
Components of Stereo Vision Systems

- Camera calibration: next week
- Image rectification: simplifies the search for correspondences
- Correspondence: which item in the left image corresponds to which item in the right image
- Reconstruction: recovers 3-D information from the 2-D correspondences

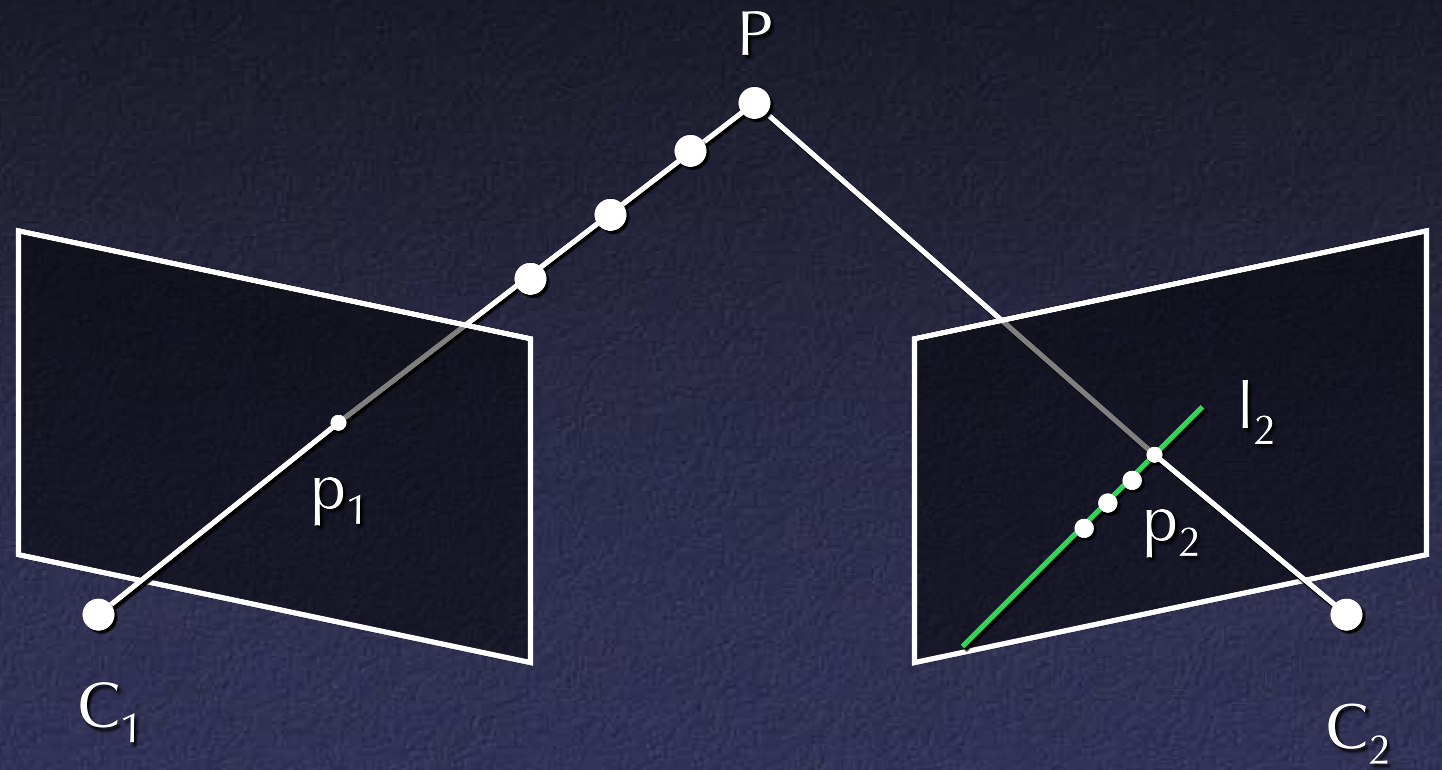
Multi-Camera Geometry

- Epipolar geometry – relationship between observed positions of points in multiple cameras
- Assume:
  - 2 cameras
  - Known intrinsics and extrinsics

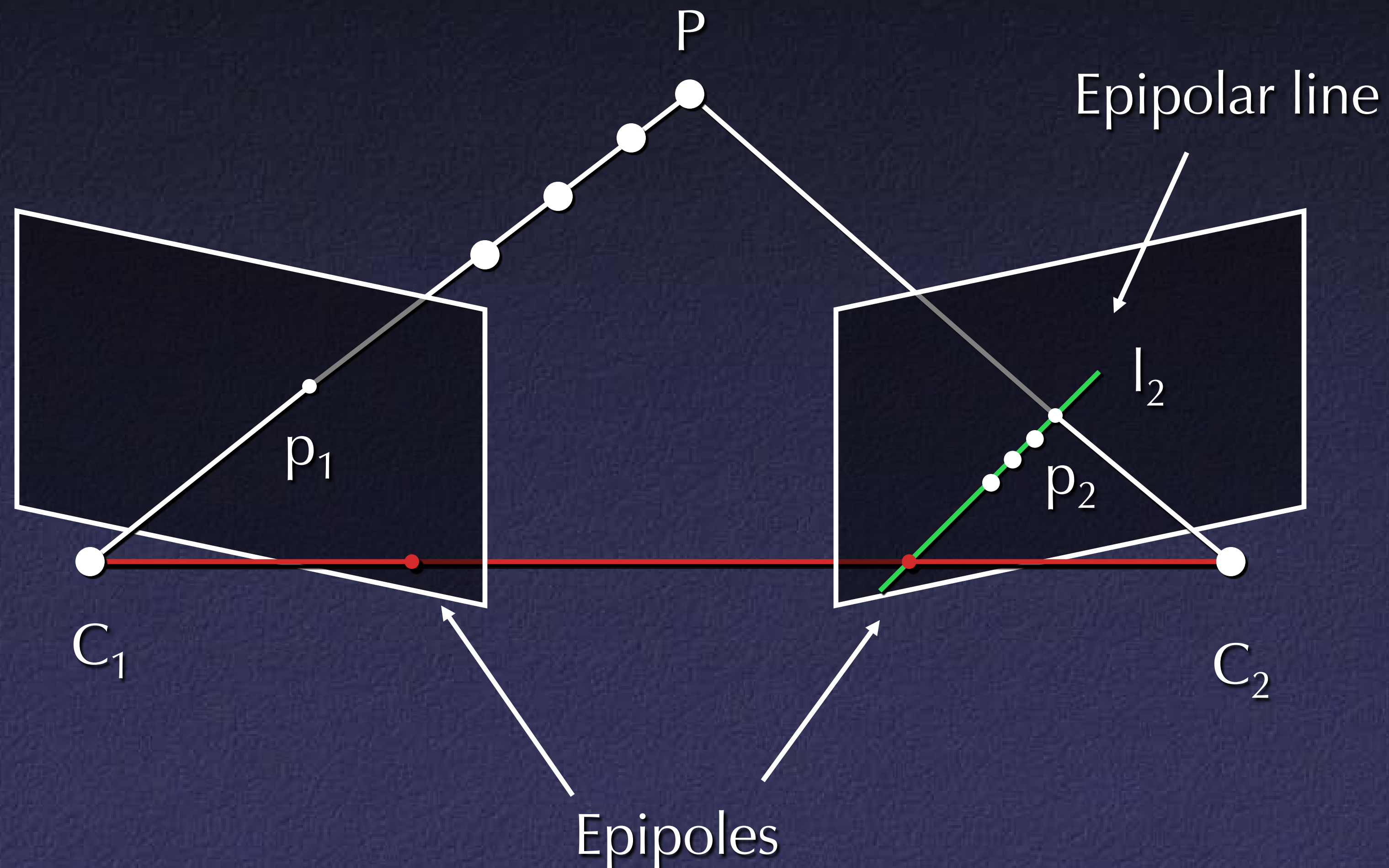
Epipolar Geometry



Epipolar Geometry



Epipolar Geometry



Epipolar Geometry

- Epipolar constraint: corresponding points must lie on conjugate epipolar lines
  - Search for correspondences becomes a 1-D problem

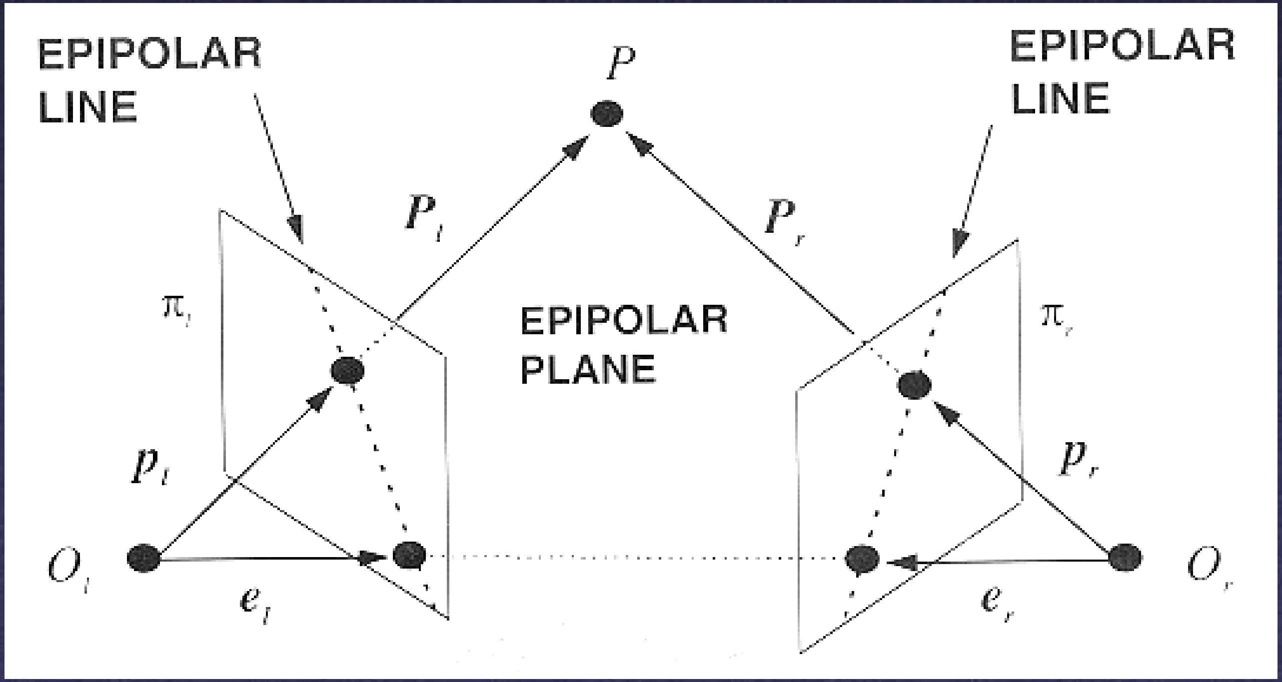
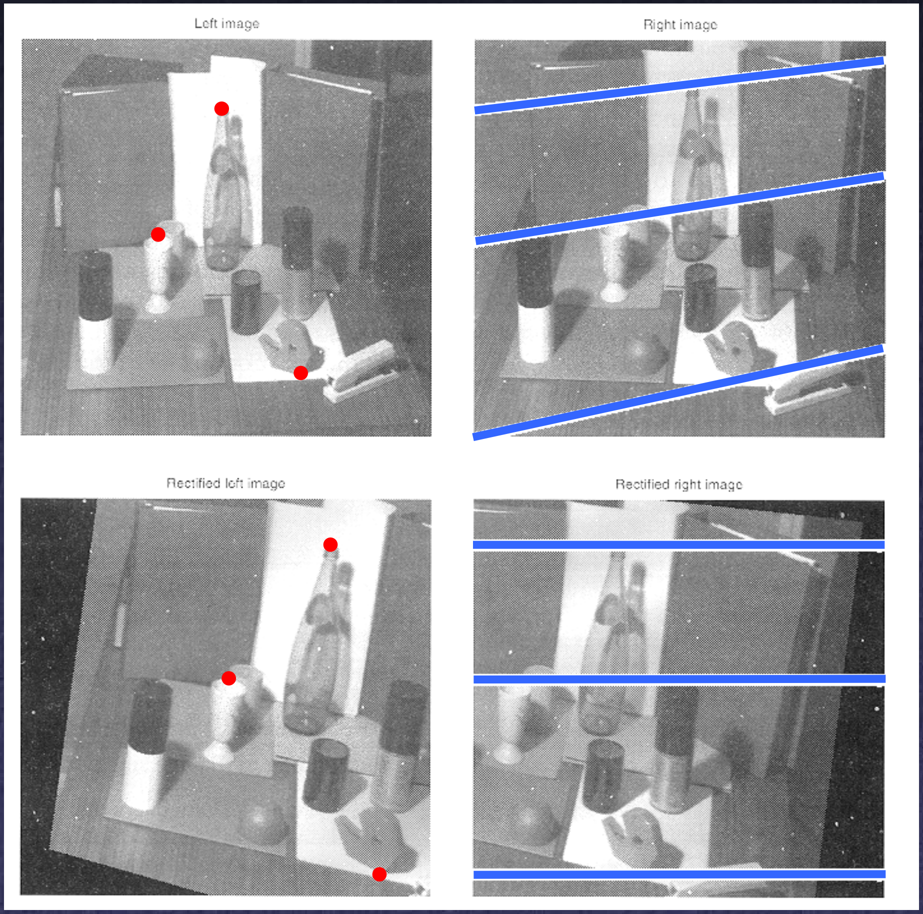


Image Rectification

- Warp images such that conjugate epipolar lines become collinear and parallel to *u* axis



Disparity

- With rectified images, disparity is just (horizontal) displacement of corresponding features in the two images
  - Disparity = 0 for distant points
  - Larger disparity for closer points
  - Depth of point proportional to 1/disparity

Correspondence

- Given an element in the left image, find the corresponding element in the right image

- Classes of methods
  - Correlation-based
  - Feature-based (next week)

Correlation-Based Correspondence

- Input: rectified stereo pair and a point (u,v) in the first image
- Method:
  - Consider window centered at (u,v)
  - For each potential matching window centered at $(u+d,v)$ in the second image, compute matching score of correspondence
  - Set disparity to value of d giving highest score

Sum of Squared Differences

- Recall: SSD for image similarity

$$\psi(u,v) = -(u-v)^2$$

- Negative sign so that higher values mean greater similarity

Normalized Cross-Correlation

- Normalize to eliminate brightness sensitivity:

$$\psi(u,v) = \frac{(u-\bar{u})(v-\bar{v})}{\sigma_u \sigma_v}$$

where

$$\bar{u} = \text{average}(u)$$

$$\sigma_u = \text{standard deviation}(u)$$

- Can help for non-diffuse scenes, hurts for perfectly diffuse ones

Window-Based Correlation

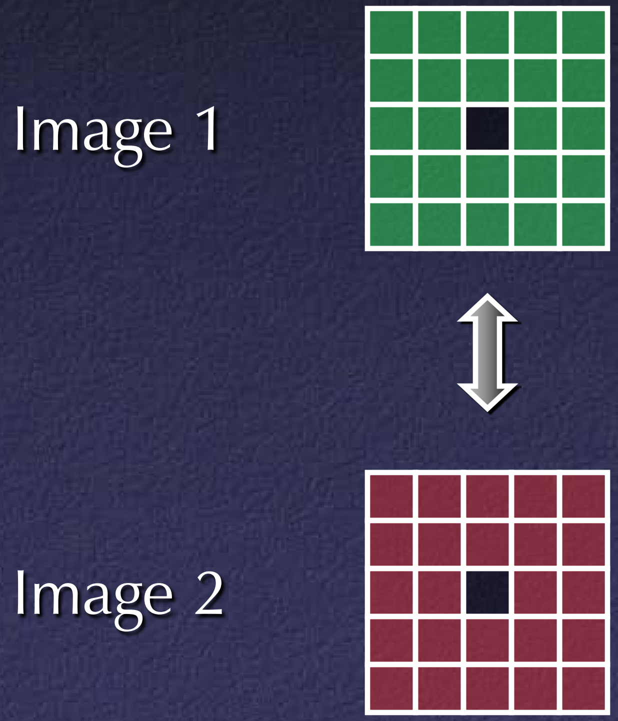
- For each pixel
  - For each disparity
    - For each pixel in window
      - Compute difference
  - Find disparity with minimum SSD

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

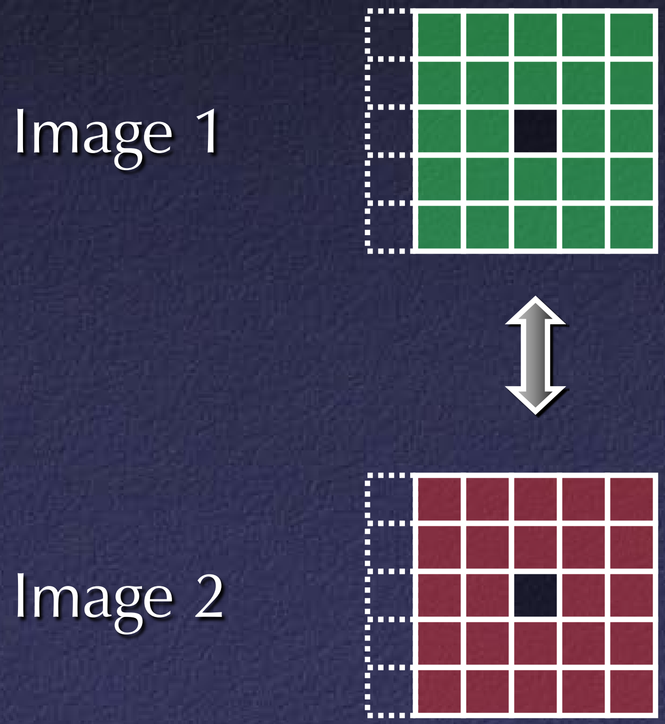
Incremental Computation

- 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

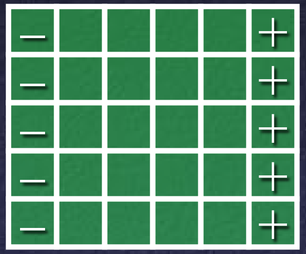
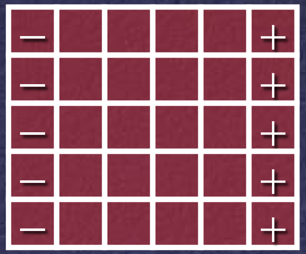


Image 2

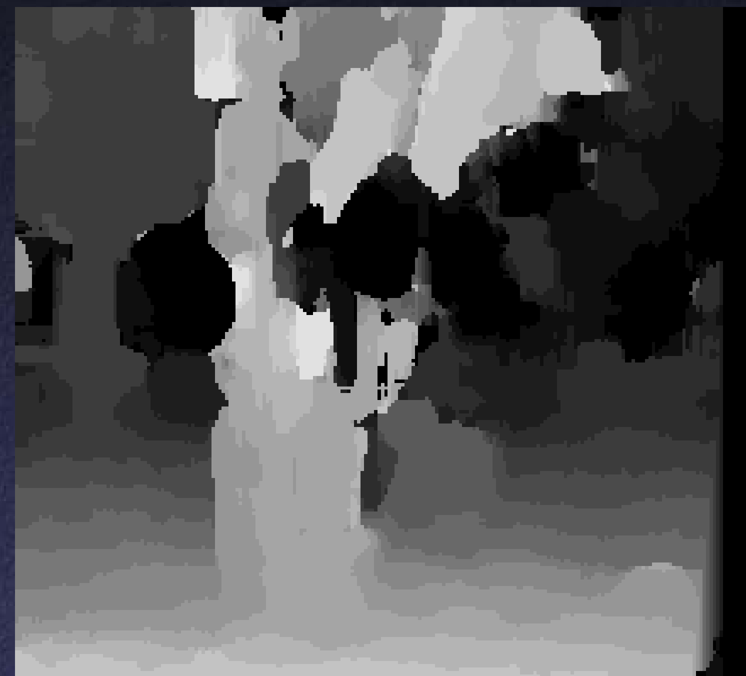


Selecting Window Size

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

Selecting Window Size

3 pixel window



20 pixel window