

Two cameras:  
Stereo and Optic Flow

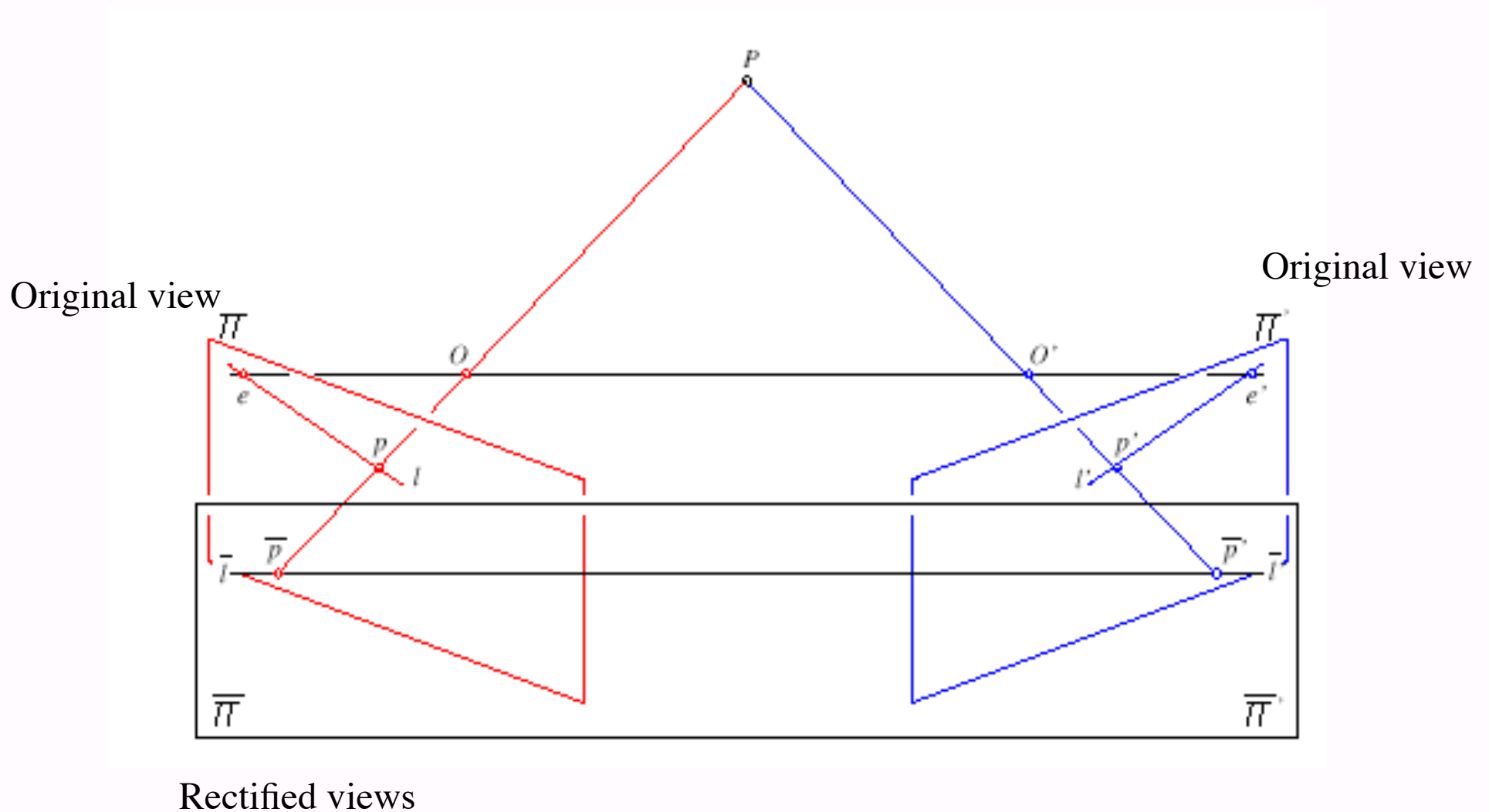
# Stereopsis

- Generically:
  - recover depth map from two images of scene
    - cameras may be calibrated/uncalibrated
      - may have large/small baseline
      - if uncalibrated, recover from fundamental matrix, above
  - do so by
    - finding correspondences
    - constructing depth map using correspondences
- Huge literature, with multiple important tricks, etc.
  - I'll mention a small set

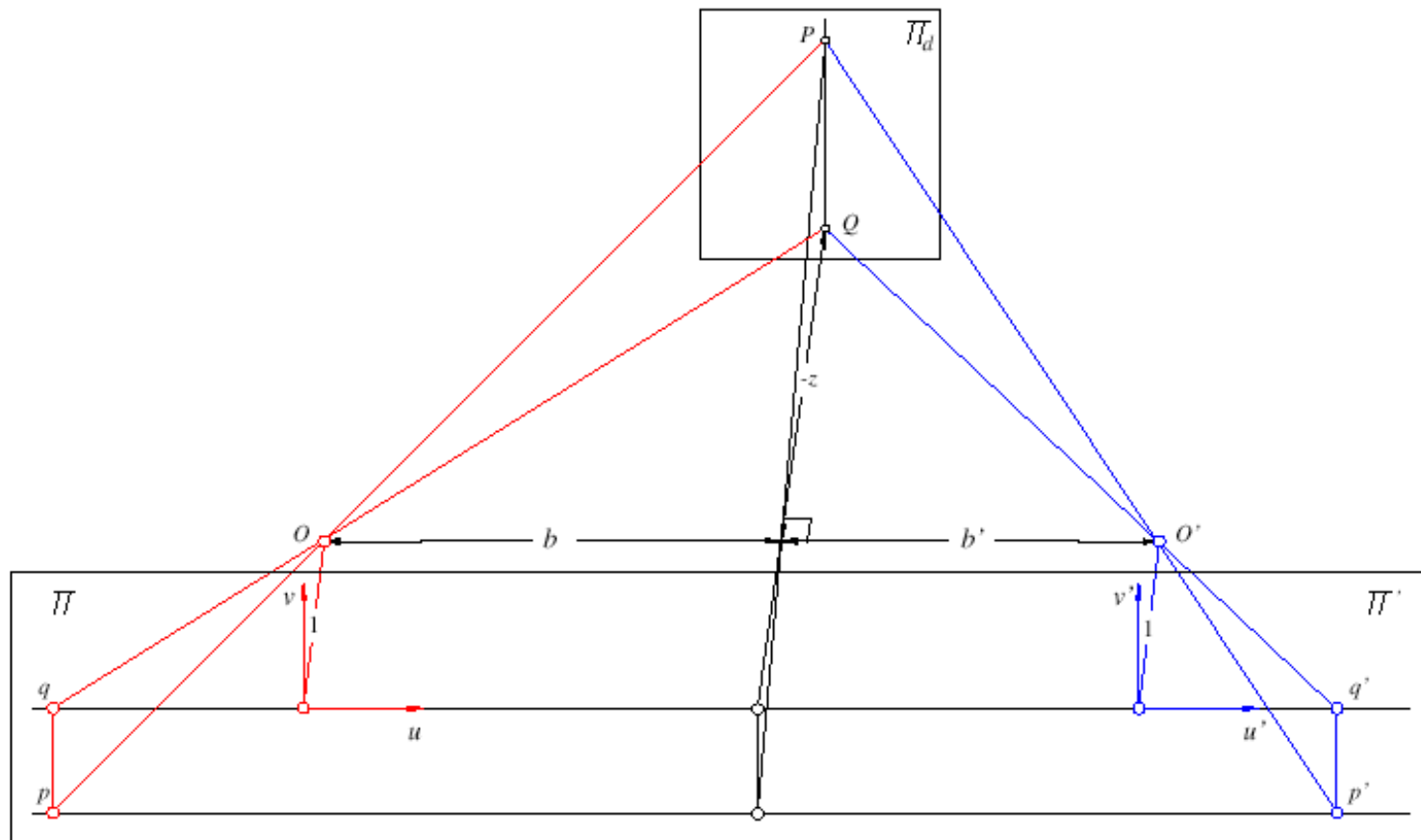
# Pragmatics

- Simplify activities by rectifying to ensure
  - That camera image planes are coplanar
  - That focal lengths are the same
  - That the separation is parallel to the scanlines
  - (all this used to be called the epipolar configuration)

# Rectification



# Triangulation

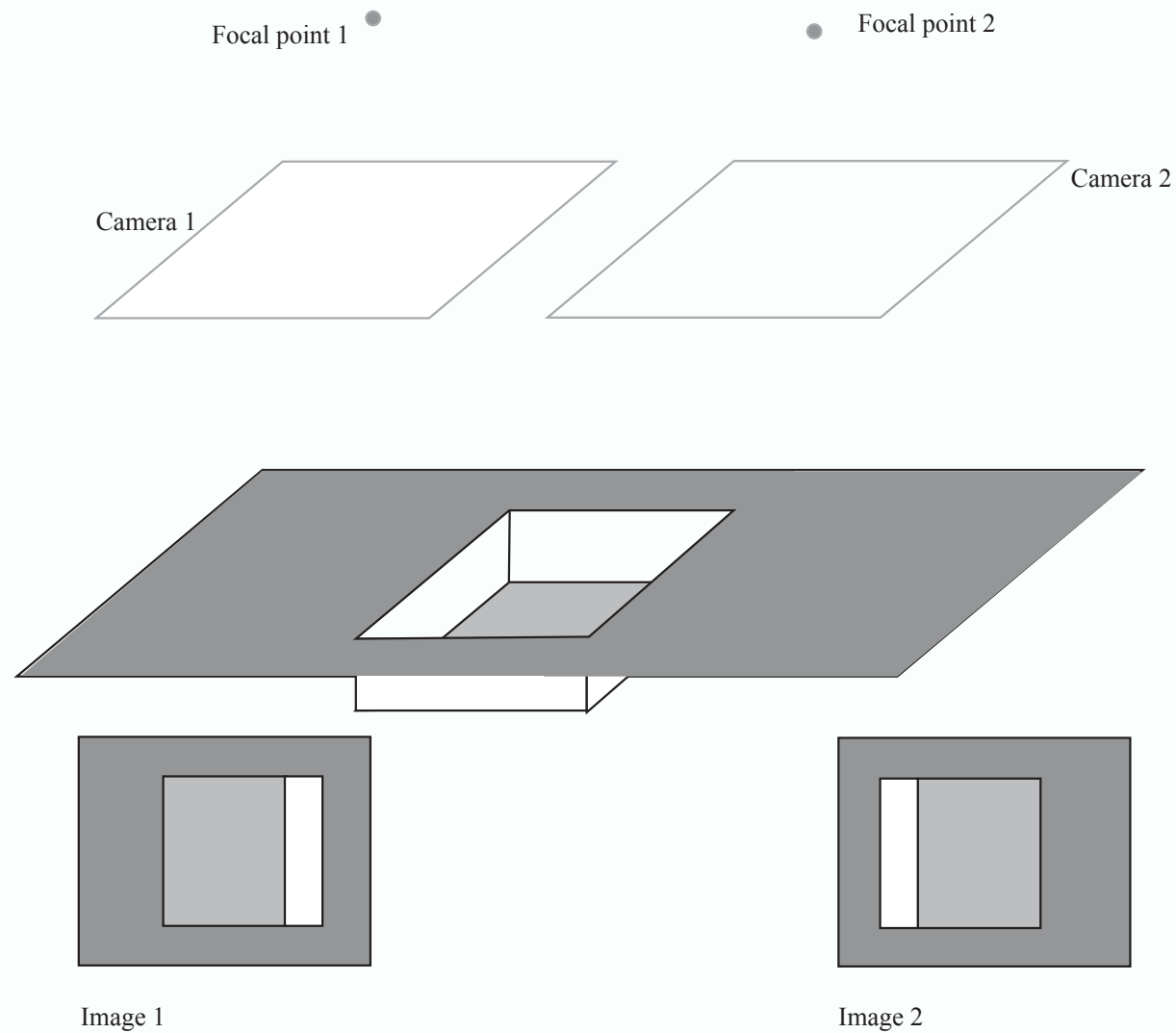


**Figure 13.6.** Triangulation for rectified images: the rays associated with two points  $p$  and  $p'$  on the same scanline are by construction guaranteed to intersect in some point  $P$ . As shown in the text, the depth of  $P$  relative to the coordinate system attached to the left camera is inversely proportional to the disparity  $d = u' - u$ . In particular, the preimage of all pairs of image points with constant disparity  $d$  is a *frontoparallel* plane  $\Pi_d$  (i.e., a plane parallel to the camera retinas).

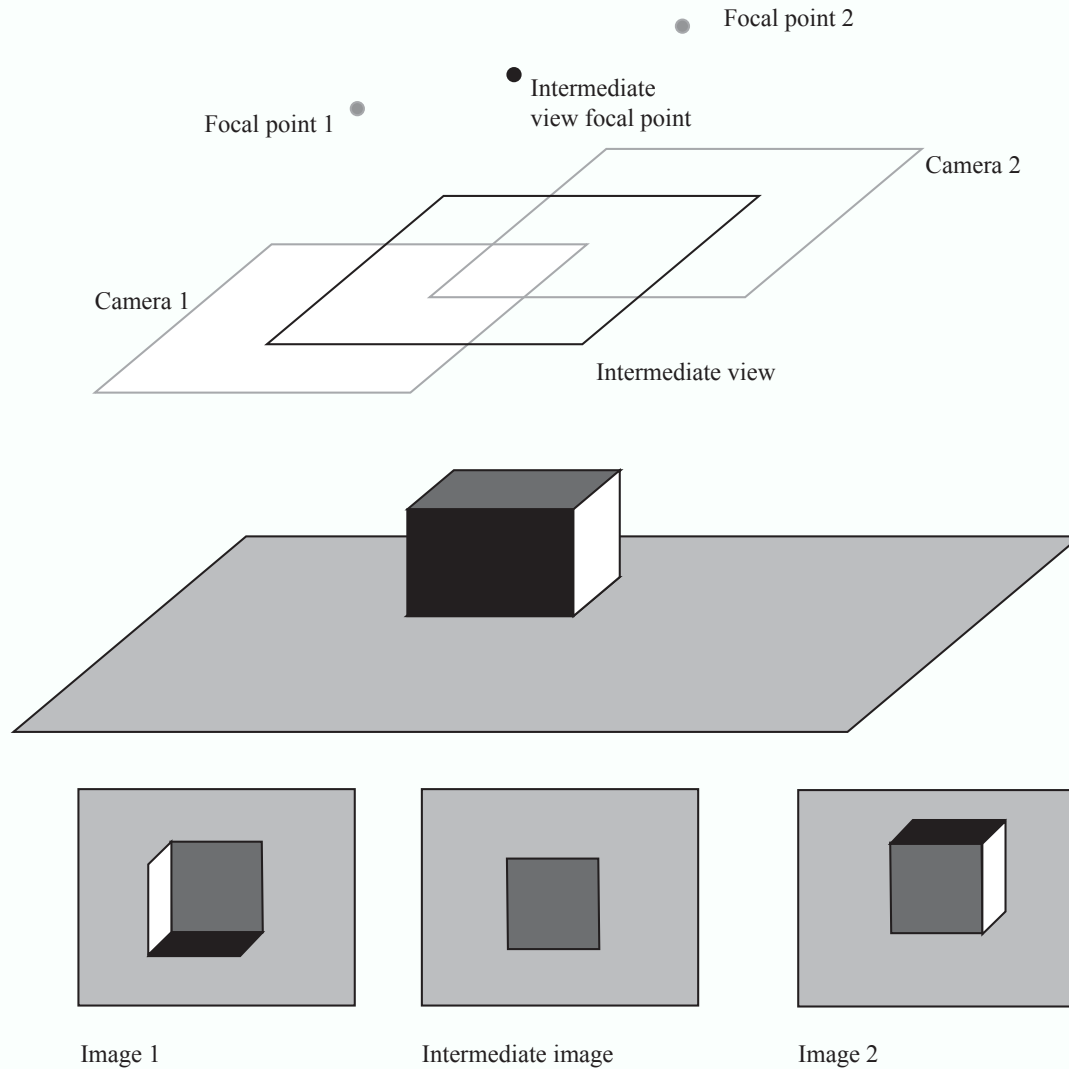
# Pragmatics

- Issue
  - Match points
- Strategy
  - correspondences occur only along scanlines
  - represent points from coarse to fine
    - scale problems - some scales are misleading
- Issue
  - some points don't have correspondences (occlusion)
- Match left to right, then right to left
  - if they don't agree, break match

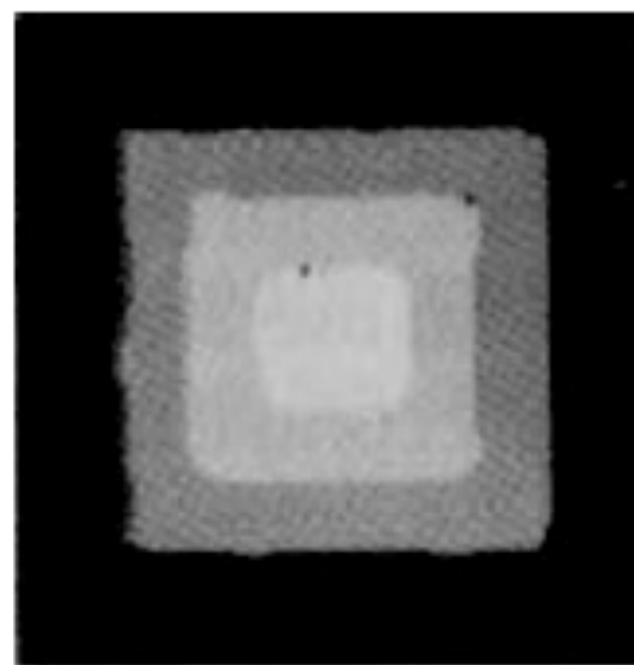
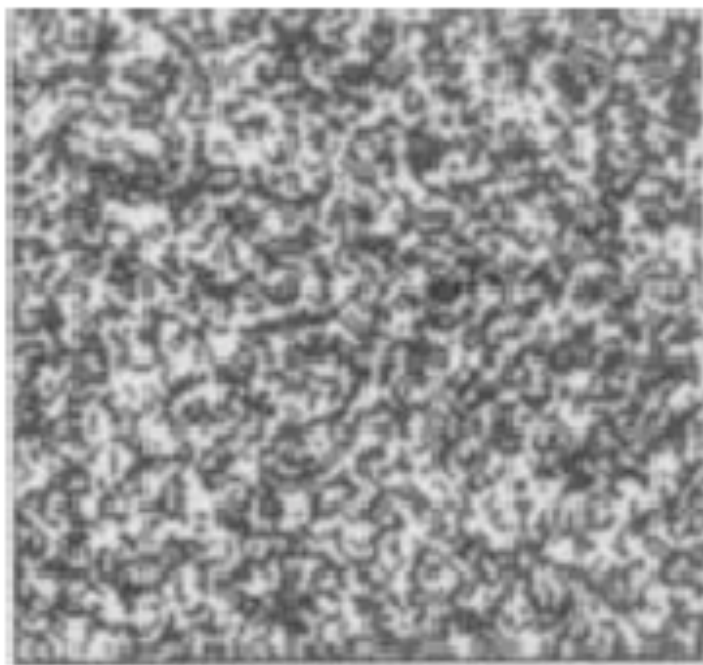
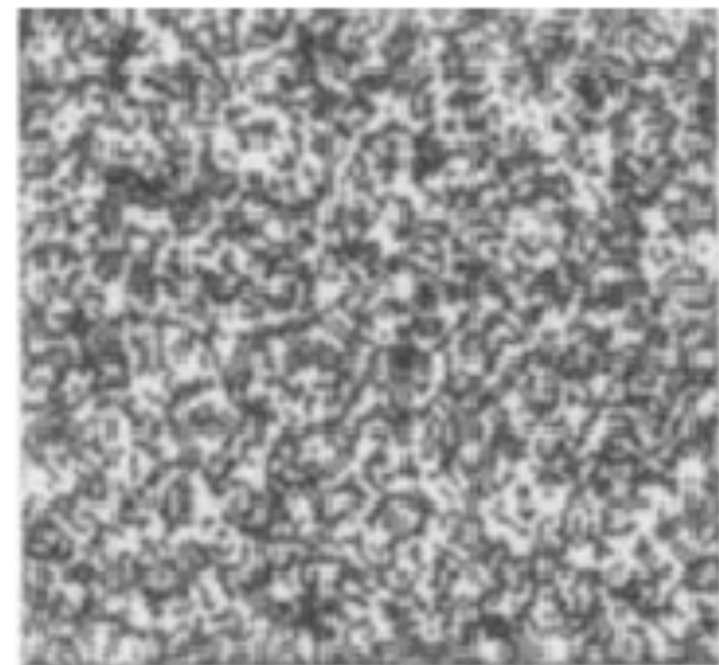
# Some points don't have matches

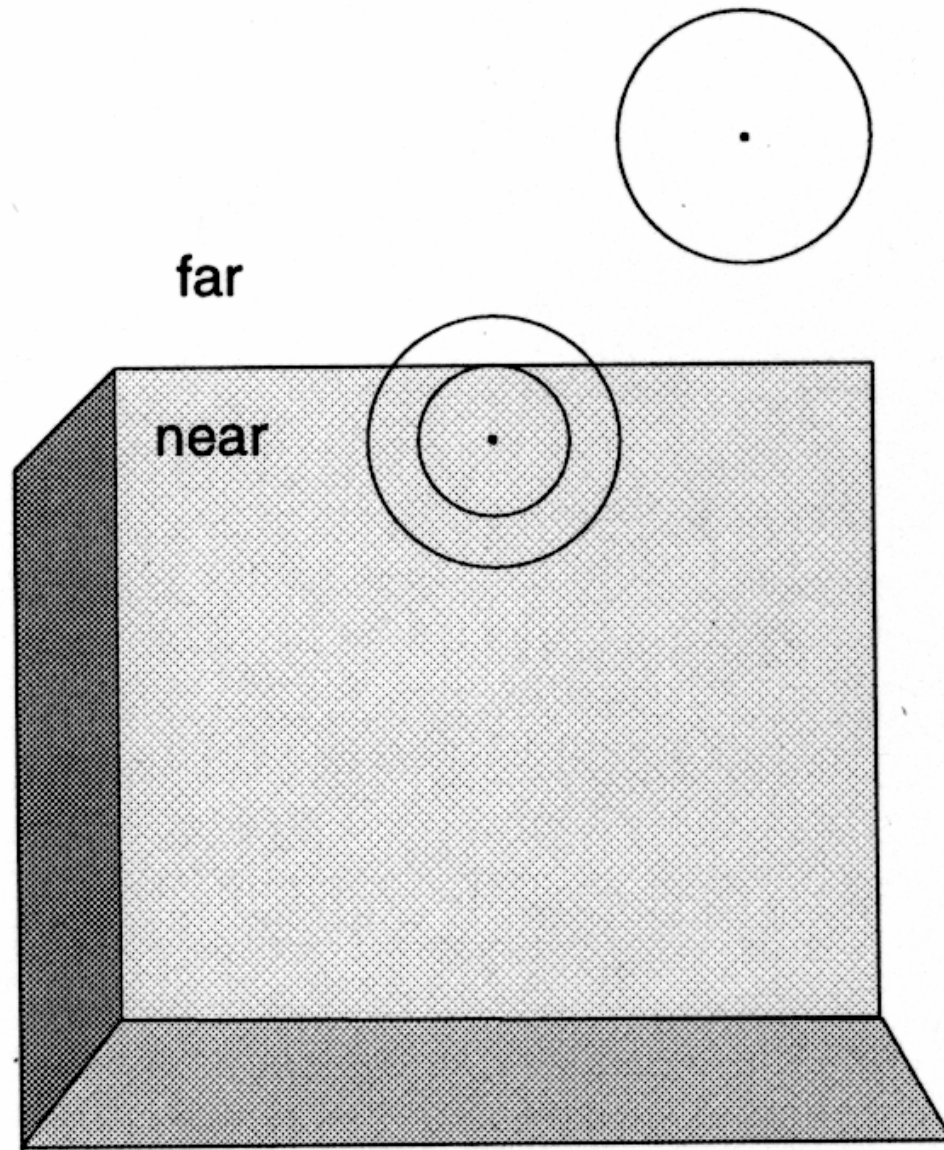


# Some points don't have matches

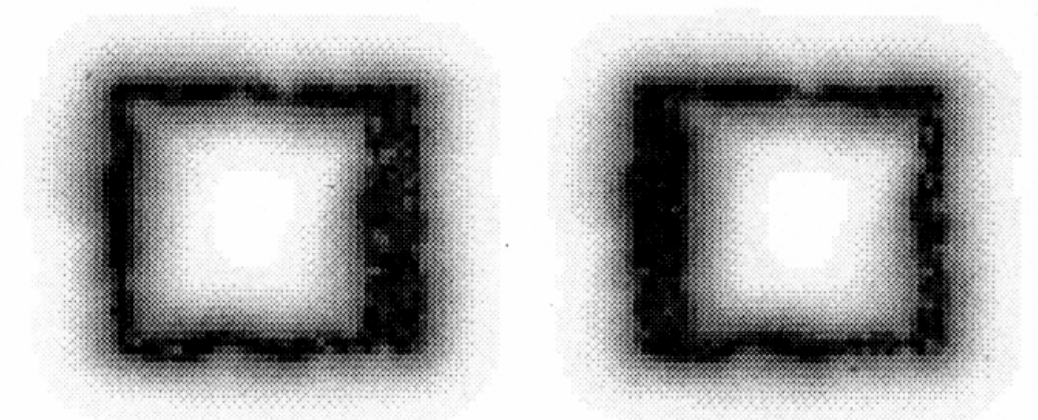
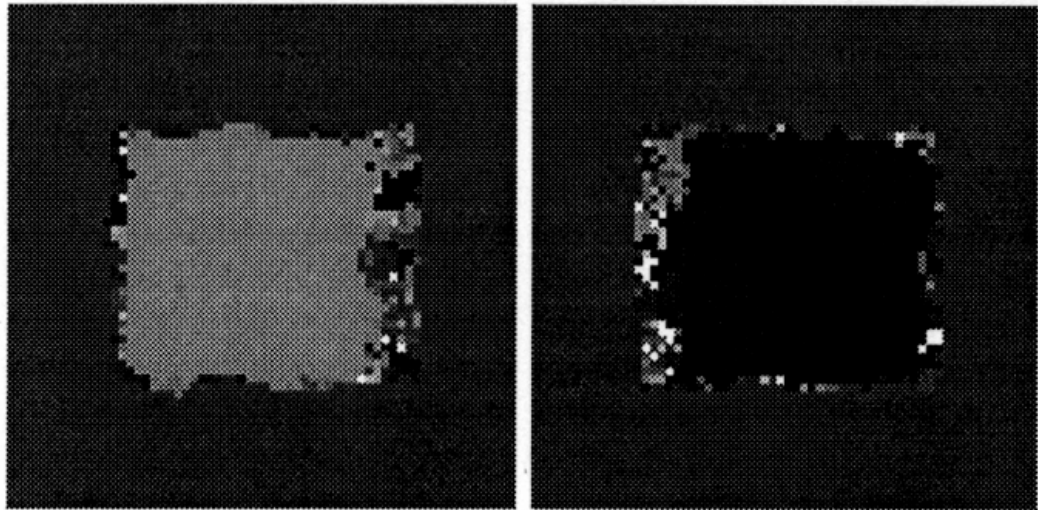




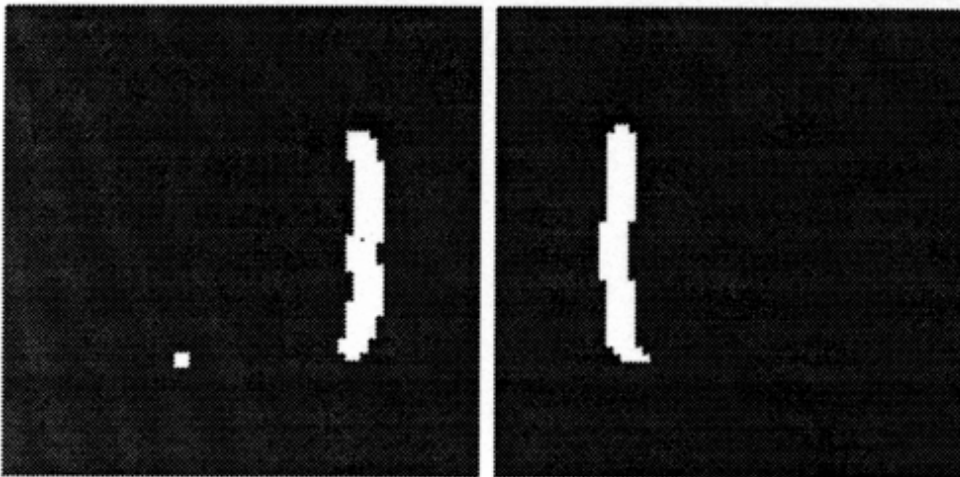
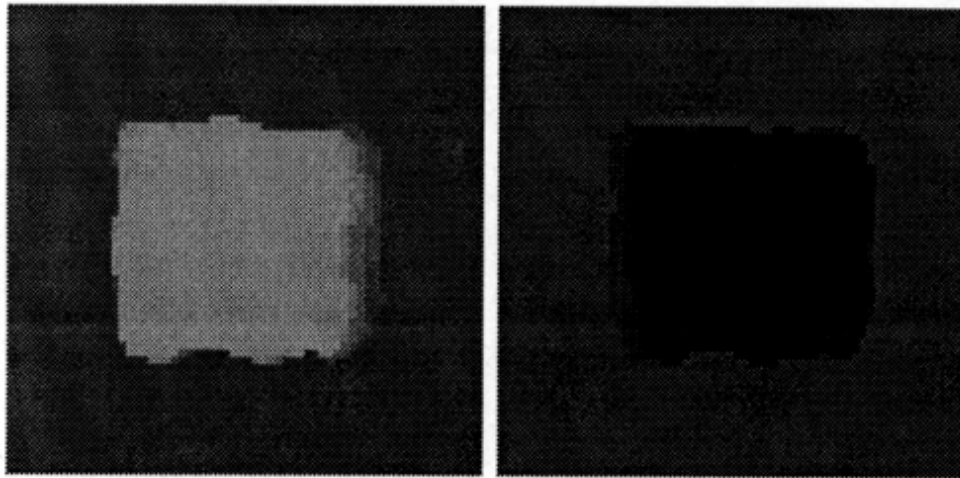




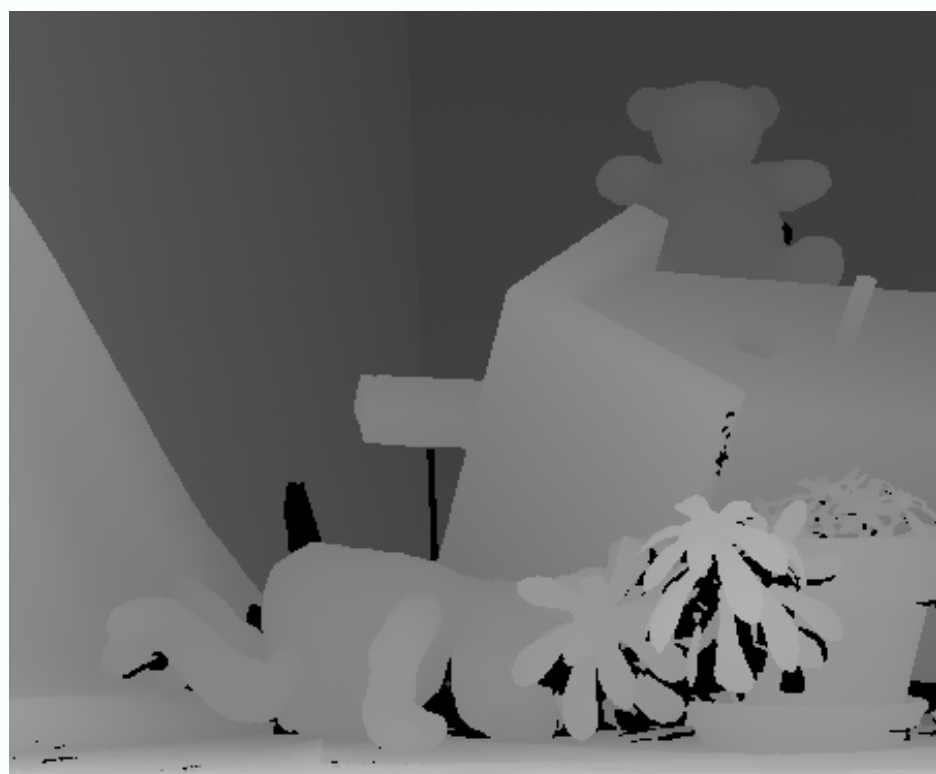
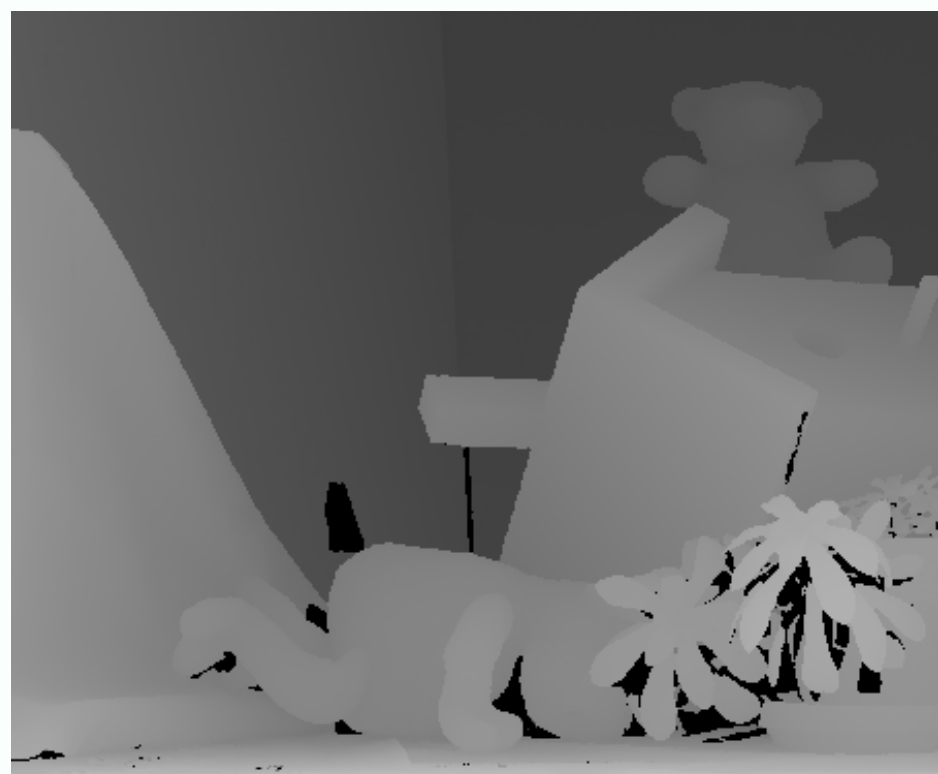
From Jones and Malik, "A computational framework for determining Stereo correspondences from a set of linear spatial filters"



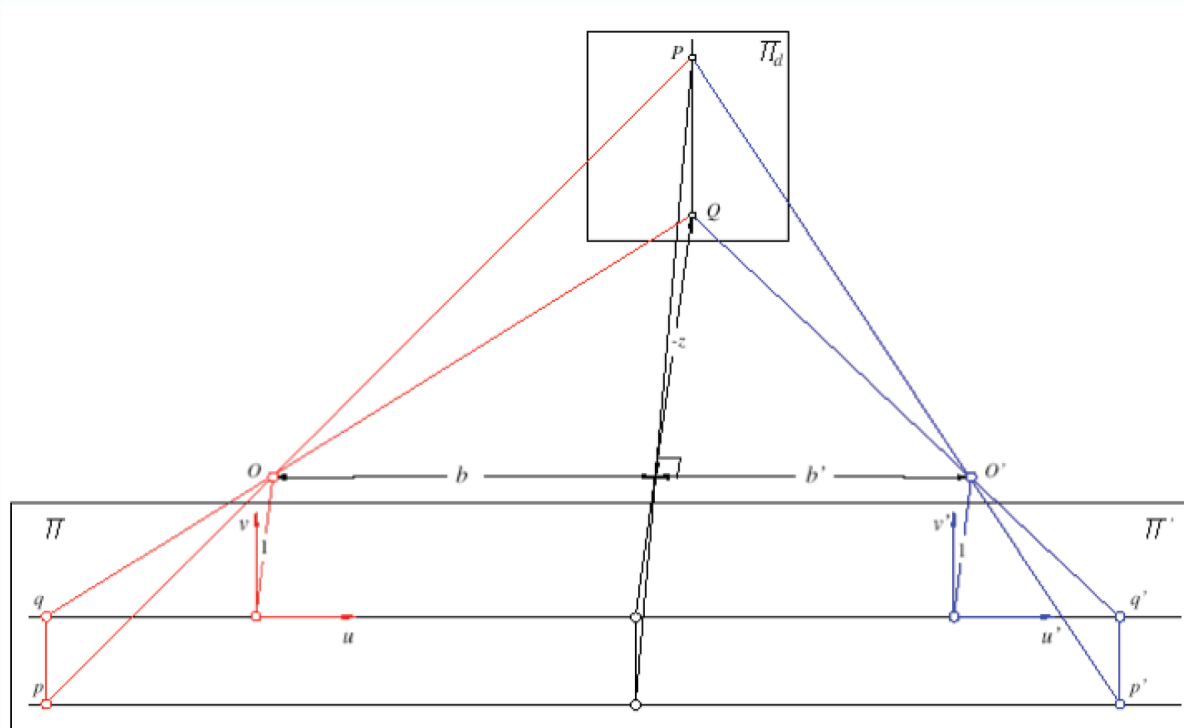
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# Stereo as an optimization problem



- Original:
  - find  $q, q'$  that match, and infer depth
- Now:
  - choose value of depth at  $q$ ; then quality of match at  $q'$  is cost
  - optimize this

# Discrete Quadratic Programs

- **Minimize:**
  - $x^T A x + b^T x$
  - subject to:  $x$  is a vector of discrete values
- **Summary:**
  - turn up rather often in early vision
    - from Markov random fields; conditional random fields; etc.
  - variety of cases:
    - some instances are polynomial
    - most are NP hard
      - but have extremely efficient, fast approximation algorithms
      - typically based on graph cuts, qv

# Stereo as an optimization problem

- Typically:
  - quantize depth to a fixed number of levels
  - unary cost is color match
    - (photometric consistency constraint)
    - it can be helpful to match intensity gradients, too
  - pairwise cost from smoothness constraint on recovered depths
    - eg depth gradient not too big, etc.
  - massive discrete quadratic program



# Stereo as an optimization problem (II)

- Segment images into regions
  - NOT semantic; small, constant color+texture
- Each region is assumed to have a linear disparity
  - $d(x, y) = a x + b y + c$
- Find a quantized “vocabulary” of such disparities
  - eg by initial disparity, incremental fitting
- For each region, choose the “best” in the “vocabulary”
  - This is a discrete optimization problem
  - It's quadratic
    - unary term - does the chosen vocab item “agree” with color data?
    - binary term - are neighboring pairs of models “similar” on boundary?

# Stereo resources

- Datasets and evaluations:
  - Middlebury stereo page has longstanding
    - datasets
    - evaluations with leaderboards
    - datasets with groundtruth
    - refs to other such collections
      - (but this is the best known, by a long way)
  - <https://vision.middlebury.edu/stereo/>

# Optic flow

- Generically:
  - a “small” camera movement yields image 2 from image 1
  - determine where points in image 1 move
- Assume we’re moving rigidly in a stationary environment
  - then points will move along their epipolar lines
    - where the epipolar lines follow from fundamental matrix
      - so from camera movement
- Main point of contrast with stereo
  - Images are not usually simultaneous
    - so objects might have moved

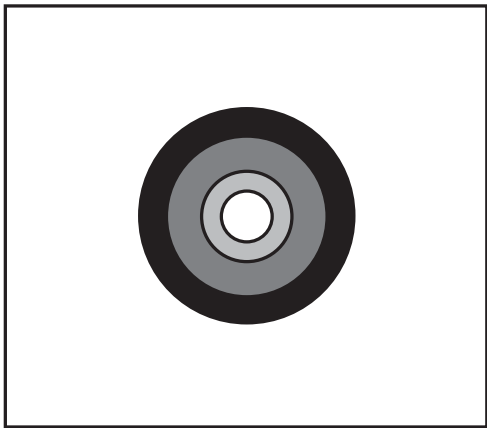
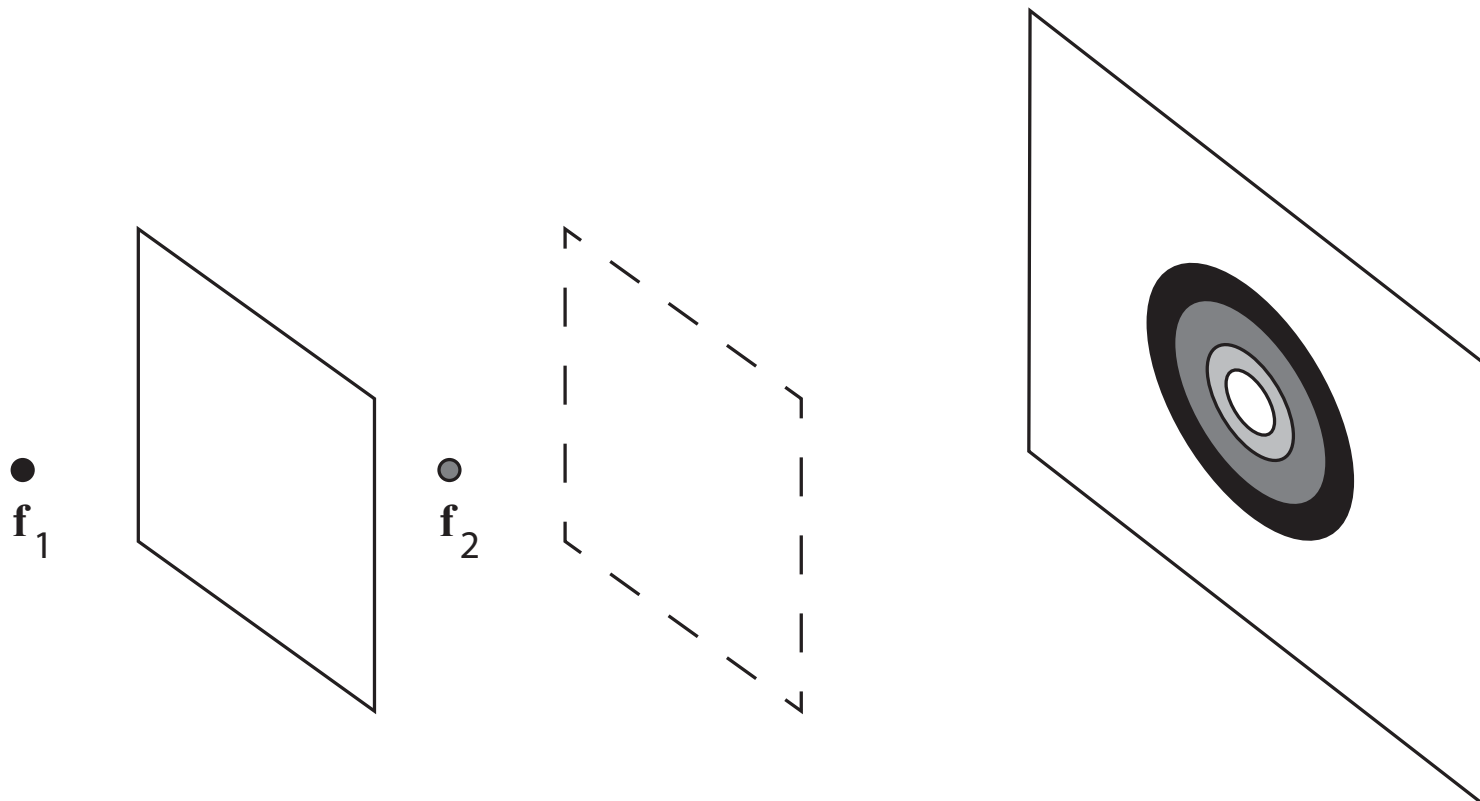


Image 1

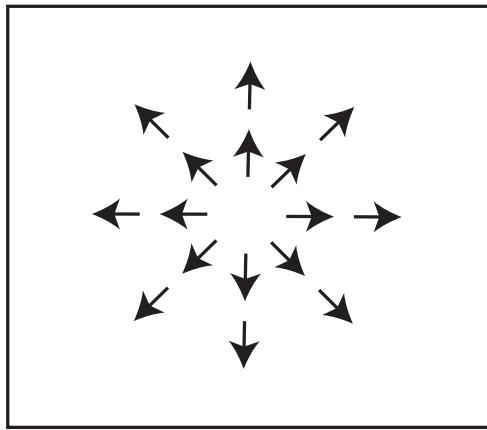


Image 1 optic flow

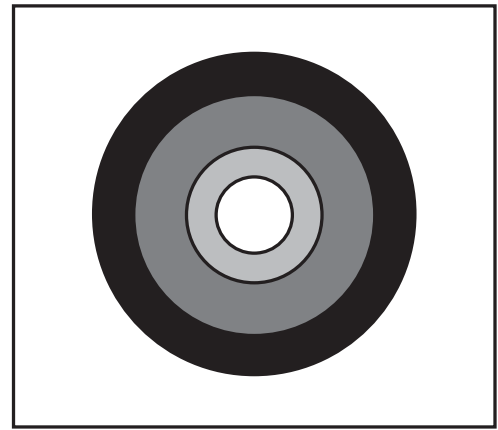
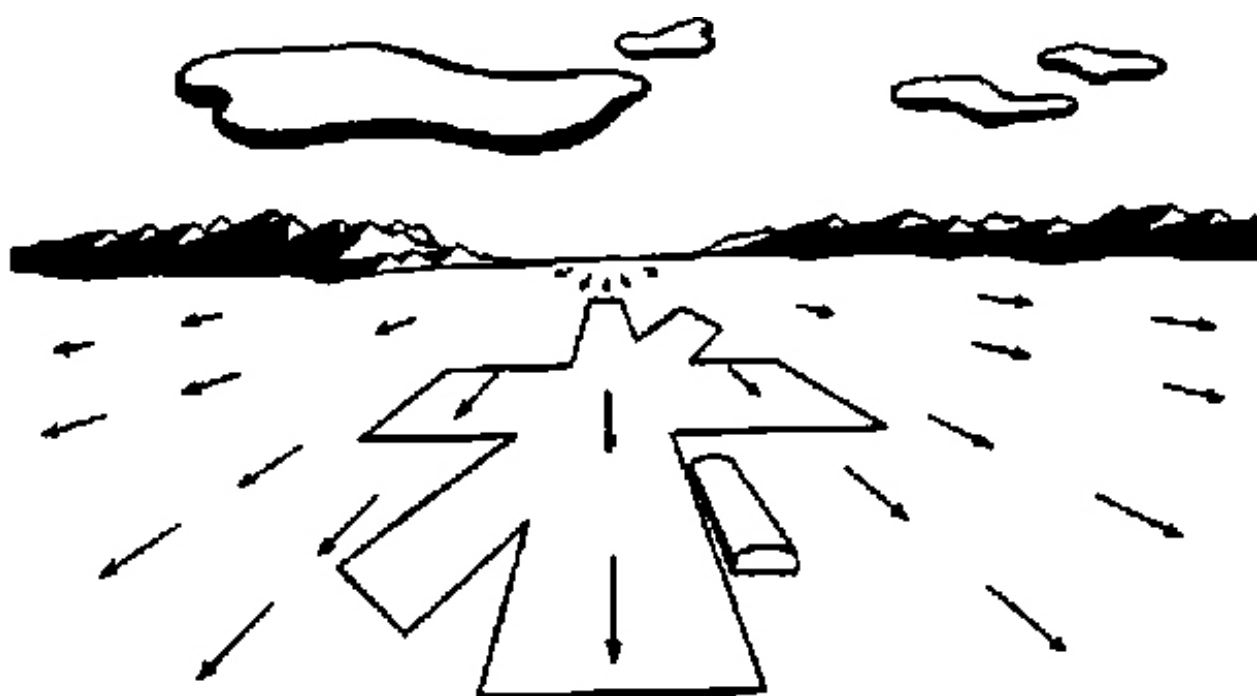
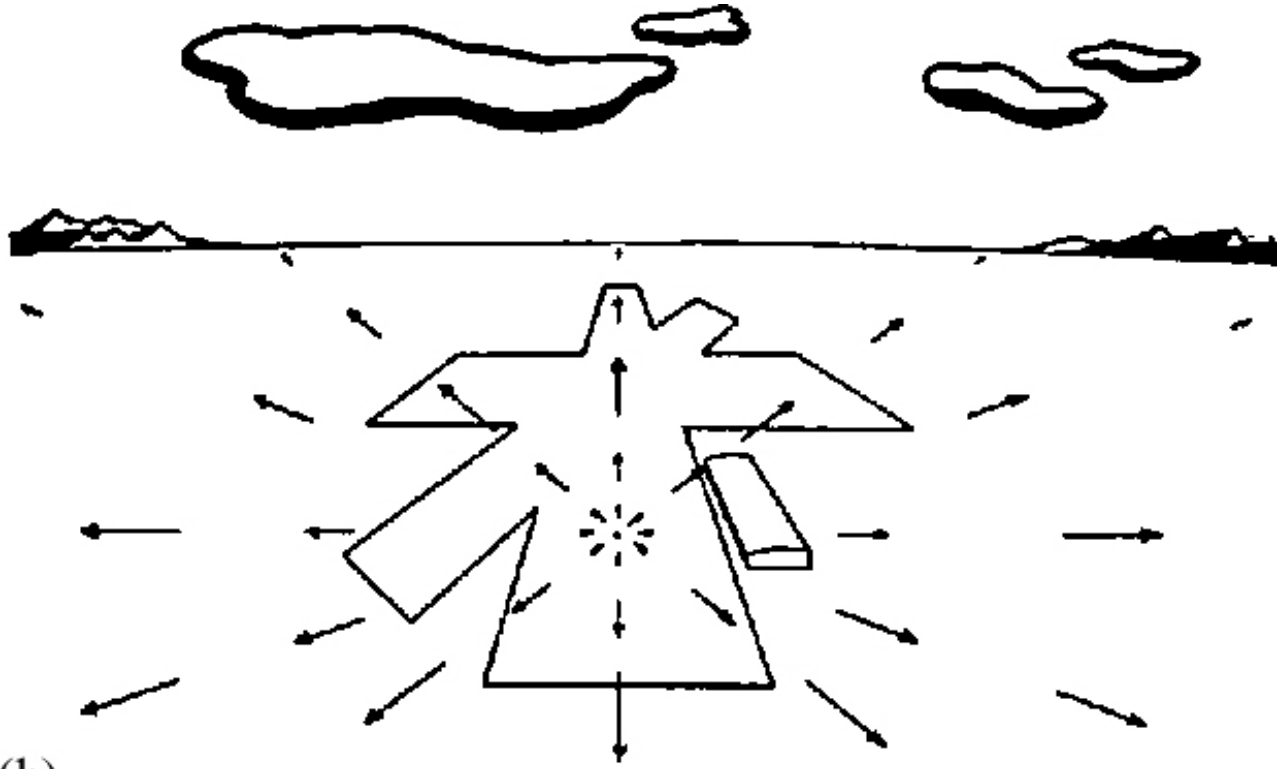


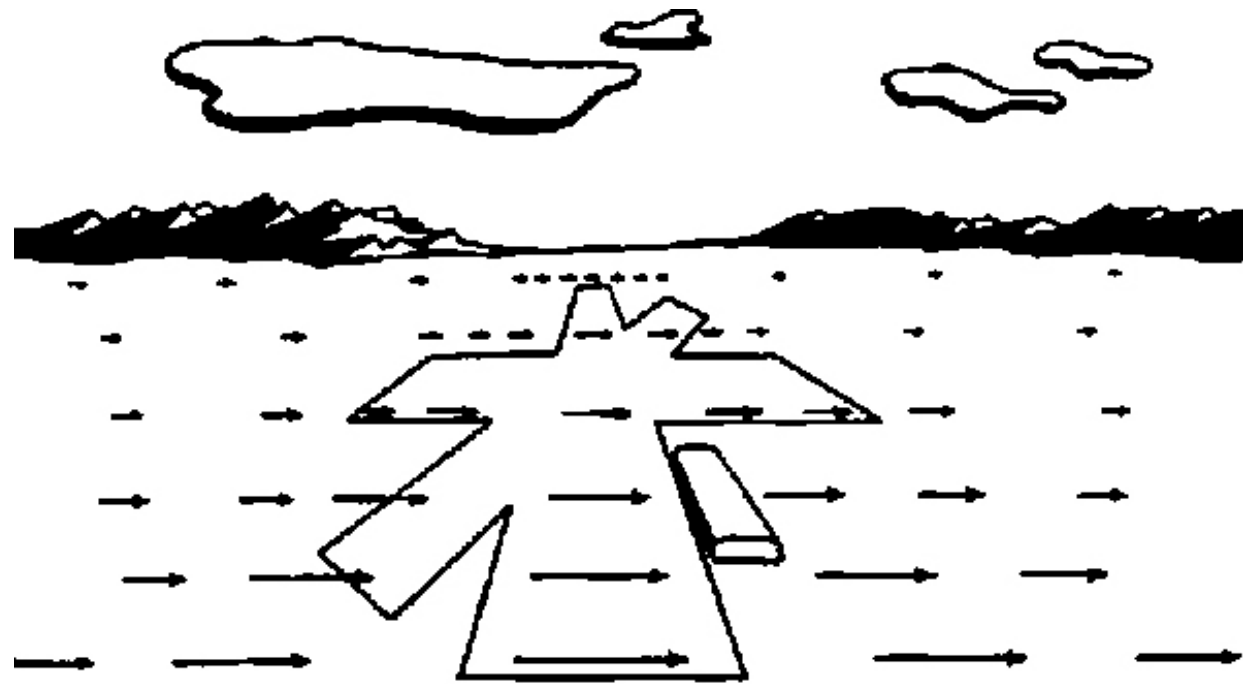
Image 2



(a)



(b)



# Optical flow

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  - then points will move along their epipolar lines
    - where the epipolar lines follow from fundamental matrix
      - so from camera movement
- As we saw, HOW FAR they move is determined by depth
  - and by their movement!!!



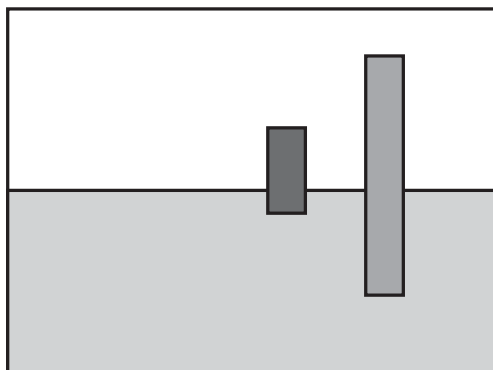
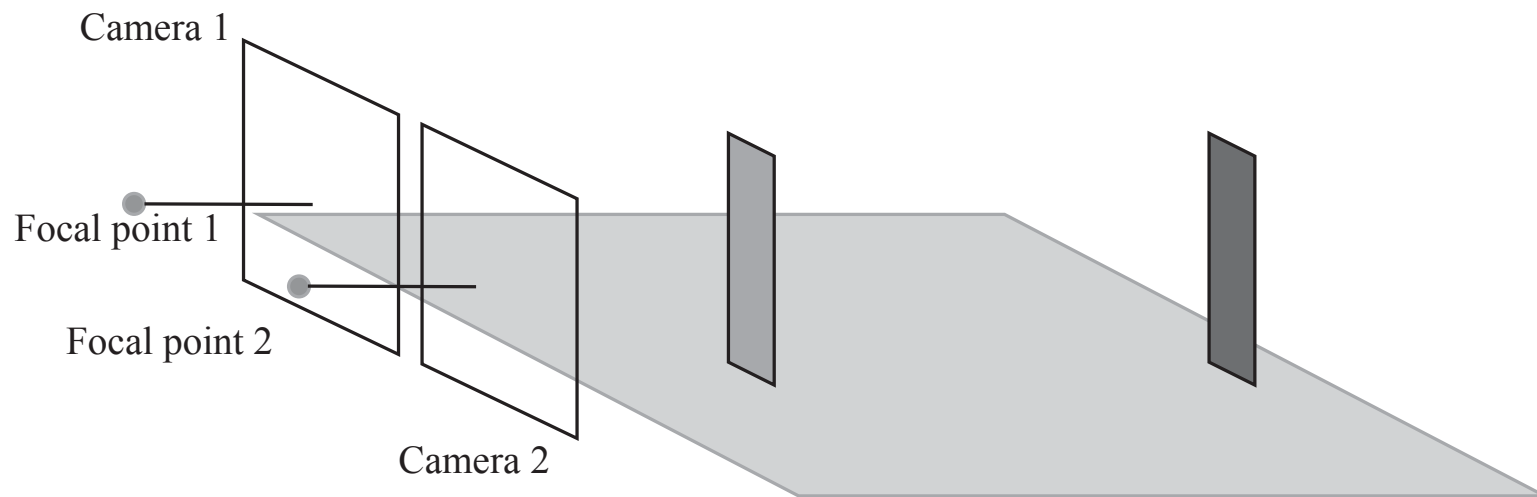


Image 1

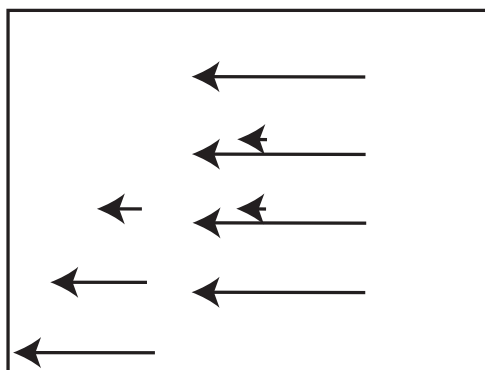


Image 1

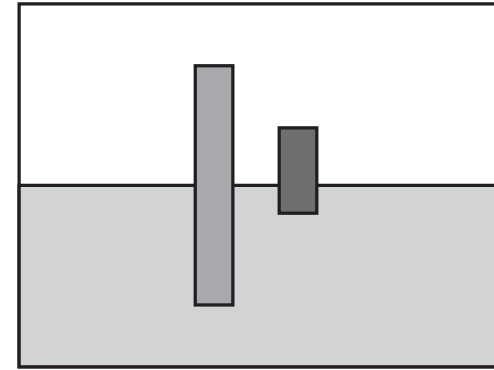


Image 2





There is flow here!



For camera motions in a rigid scene, you can determine ground truth.  
Evaluation is then by comparison to ground truth.

# Recovering optic flow

- Huge literature
- Initial strategy:
  - Assume

Image gradients

$$\frac{dI(x, y, t)}{dt} = \frac{\partial I}{\partial x} \frac{\partial x}{\partial t} + \frac{\partial I}{\partial y} \frac{\partial y}{\partial t} + \frac{\partial I}{\partial t} = 0$$

Flow (which is unknown)

$$I_x u + I_y v + I_t = 0$$

# Recovering optic flow

- Strategies:  $I_x u + I_y v + I_t = 0$ 
  - find  $u(x, y), v(x, y)$  that minimizes some smoothness cost
    - subject to constraint on flow
    - what smoothness cost?
    - how to impose constraint?
  - assume flow has some parametric form within windows (eg. constant)
    - choose parameters to minimize error in window
    - what parametric model?
    - what windows?
  - If few or no objects move
    - impose a parametric depth model, and use that





If objects are moving, much harder to determine ground truth.

IDEA: Interpolate flow to get intermediate frame.

Evaluation is then by comparing interpolate to ground truth frame.



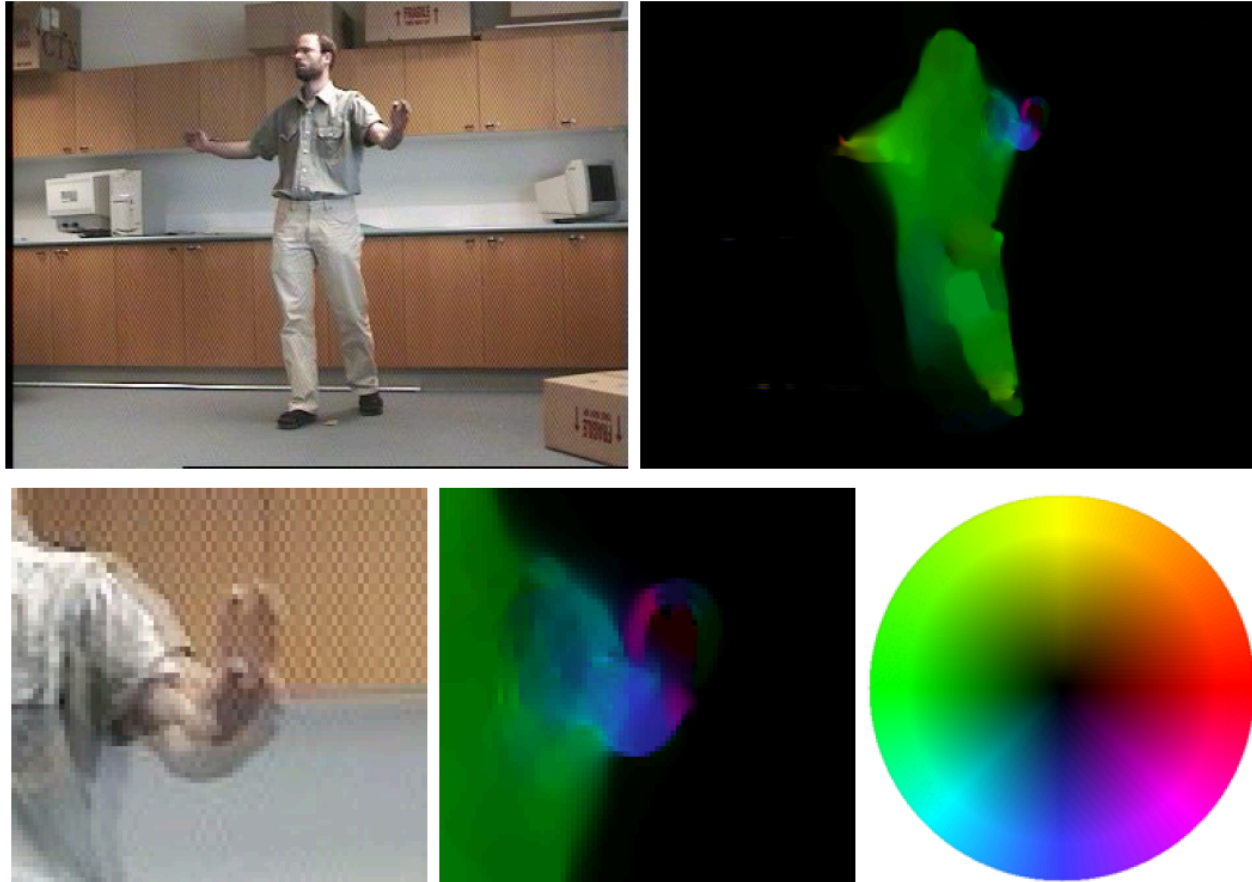


Figure 1. **Top row:** Image of a sequence where the person is stepping forward and moving his hands. The optical flow estimated with the method from [4] is quite accurate for the main body and the legs, but the hands are not accurately captured. **Bottom row, left:** Overlay of two successive frames showing the motion of one of the hands. **Center:** The arm motion is still good but the hand has a smaller scale than its displacement leading to a local minimum. **Right:** Color map used to visualize flow fields in this paper. Smaller vectors are darker and color indicates the direction.



# Strategy

- Segment into regions, estimate region correspondences
  - use to inform flow estimate

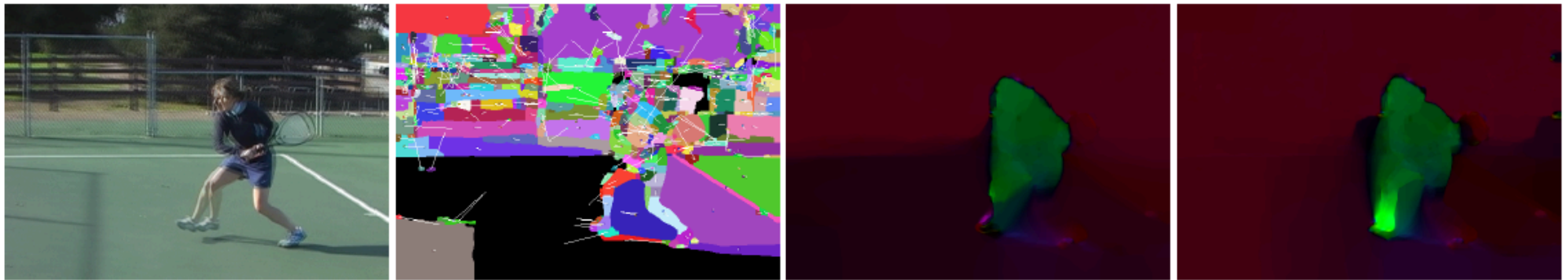


Figure 9. **Left:** Two overlaid images of a tennis player in action. **Center left:** Region correspondences. **Center right:** Result with optical flow from [4]. The motion of the right leg is too fast to be estimated. **Right:** The proposed method captures the motion of the leg.

# Optical flow resources

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